RESEARCH PAPER

EDGE-INTELLIGENT WALL-MOUNTED IOT SURVEILLANCE SYSTEM FOR REAL-TIME STRAWBERRY DISEASE DETECTION

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ABSTRACT
Plant diseases need to be identified early to help in safeguarding crop yield and to encourage sustainable farming methods. In the process of strawberry farming, early detection is usually followed by a rapid spread of the disease and a high cost. In this paper, the author will describe a wall-mounted edge-intelligent IoT surveillance system that is capable of being deployed to constantly monitor the real-time status of strawberry plants in field settings. The suggested system substitutes manual inspection with an automated fixed position monitoring model with an integrated embedded vision hardware and lightweight deep learning. A SqueeNet-based classification network is trained in a manner that it is capable of identifying various diseases of a strawberry plant and executes effectively on resource-limited edge devices. In order to facilitate real-time operation, the UDP-based communication mechanism is used to relay detection results in the least amount of latency. An on-site alert unit which is an LCD display and a buzzer is also built into the system to allow the farmers to be able to obtain immediate feedback and make appropriate action. The proposed architecture, unlike solutions of agricultural monitoring that rely on clouds, integrates local edge processing in order to minimize energy consumption, network reliance, and response time. The experimental results demonstrate that the system is effective with regards to a reliable classification accuracy, constant performance, and rapid detection response in real-world conditions. The findings indicate that the suggested solution can be deployed in the smart farming and precision farming solutions in large-scale applications.
Keywords: Smart agriculture, strawberry disease detection, edge computing, IoT monitoring, ShuffleNet, plant disease classification, real-time surveillance, precision farming.
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I. INTRODUCTION

The influence of strawberry on the economy of contemporary agriculture is significant; however, this crop is severely affected by leaf diseases, which may lower crop quantity and quality considerably. Early disease detection is thus very vital in the management of farms and effective treatment. The manual inspection approaches are time-consuming, subjective and not applicable in monitoring large areas, a factor that is encouraging the use of computer vision systems of smart agriculture to be automated. Recent developments in deep learning have shown good results in recognizing plant diseases especially with convolutional neural networks (CNNs) and object detection systems. A number of studies have been dedicated to enhancing the accuracy of detection based on advanced model structures. Rouf et al. have suggested an ensemble structure that involves YOLOv8, EfficientNetV2, and DeepLabV3+ to detect, classify and segment in the same task, which allows characterizing the disease in strawberries in a holistic manner [1]. In the same way, Ramdani and Suyanto used a ResNet-50 CNN-based model to classify strawberry leaves and achieved almost perfect accuracy on controlled data, which showed that deep learning can be effectively used in disease recognition [2]. Nevertheless, the complexity of the models and the high cost of the computations can frequently make deployment in practice in an agricultural setup. Edge-based solutions have come up in order to overcome resource limitations and latency issues. Bouchnafa and Amnai discussed CNN and Vision Transformer designs to operate on edges, and they pointed out the trade-off between accuracy and computation efficiency, where lightweight CNNs provide a viable benefit to edge computing systems [3]. Crop monitoring by drones has also received interest; Shaad et al. have shown real-time disease detection with NCNN-optimized YOLO models on embedded hardware using the models to achieve better throughput and long-term field capability [4]. Moreover, detection frameworks, like enhanced YOLOv7 model by Yang and Duan, optimize detection and the model is established with multi-scale perception and with low computational costs [5]. Although these innovations have taken place, most of the current systems are based on mobile platforms or cloud computing which provide latency, lack of connectivity, and scalability problems. There is also a necessity of fixed-position, edge-intelligent surveillance systems, which ensure constant monitoring and feedback to the farmers in real-time. In this paper, the lightweight deep learning, wall-mounted IoT deployment, and real-time alert systems are systematically implemented to fill this gap and create a real-world agricultural monitoring system.

II. RELATED WORKS

More recent studies in plant disease detection have moved towards small-scale deep learning models that may be used in real-time in agricultural settings. Devi et al. proposed a layer weight regularized Orthogonal Layer ThresholdedReLU DenseNet (TODN) architecture to predict strawberry diseases by using a better regularization and activation method, with high classification accuracies [6]. Although the state of their approach proved to be highly effective in a controlled dataset, the system focused on offline classification instead of in-field monitoring constantly and IoT deployment in general. Explainable and lightweight deep learning models have also been used in fields. Biswas et al. have suggested a small CNN-based structure to classify Java Apple leaf disease, using GradCAM and Ablation-CAM visualization to guarantee the interpretability of the decisions [7]. In their work, the authors emphasize the role of deployable architectures and transparency in real-world agriculture. In the same way, Rahman et al. designed an augmented enhanced CNN with attention mechanism (AECNN-A) optimized on mobile edge devices to attain the competitive accuracy with minimized computational cost [8]. Attentional extraction of features can result in superior localization of the disease regions as well as scalability to low resource settings.

Efficient architecture transfer learning has been successful in crop diagnostics. Shrivastava et al. proved the accuracy of a fine-tuned MobileNetV2 model to be high in the guava leaf disease classification and the model did not reduce computational performance, which was appropriate in the real-time application [9]. Their results support the usefulness of lightweight networks in precision agriculture, especially in situations where there are energy and hardware-related constraints. In addition to the classification, edge-based systems of IoT image processing are becoming feasible in crop monitoring. The article by Sendra et al. introduced a vision system based on Raspberry Pi, which incorporates the data of environmental sensors to detect changes in the state of the leaves, and demonstrates the effect of multimodal IoTs on detection reliability [10]. Nevertheless, they concentrated on brightness-based analysis instead of profound classifying the disease with the use of neural networks. Deep neural networks still feature in the middle stage of automated plant disease diagnostics in various types of crops. Shobana et al. used a DenseNet-based deep neural network to classify the diseases of multi-crops and proved to be more accurate than traditional inspection methods [11]. Their system confirmed the relevance of deep architectures to a wide range of agricultural data, but the research was mainly done regarding offline prediction and did not consider the limitations of deploying the system to edge or IoT systems.

Hybrid learning approaches have also been utilized in disease modelling of strawberry. Alajas et al. presented a recurrent neural network framework based on a population to detect Diplocarpon earlianum infection and estimate the rate of infection of the leaf region [12]. They combined feature selection and evolutionary algorithms in their hybrid pipeline of optimization that enhanced the reliability of prediction. Although the method was very specific and effective in terms of accuracy and quantitative estimation of the infection, its algorithms have high computational cost and can take a long time to compute, which makes the method impractical in real-time usage in the field. Massive dataset-based classification has also enhanced the study of plant-diseases. Appavu also examined hybrid deep learning models based on VGG16 and the PlantVillage dataset and reported high classification accuracy based on large-scale augmentation and architecture comparison as the means to achieve high classification accuracy [13]. In a similar manner, Prasad et al. used CNN-based image classification and integrated IoT sensors to allow crop health monitoring remotely, which proves the advantages of multimodal agricultural diagnostics [14]. These articles emphasize the increased intersection of AI and IoT in precision agriculture but are based on high-resource or centralized processing. Preprocessing and segmentation are still essential elements of the pipelines of plant disease. Pal et al. put forward an edge-based color feature extraction model to crop segmentation which works around the illumination variation and background noise in practical image [15]. They have highlighted the need to have a strong preprocessing to have a good downstream classification.

According to recent studies, the use of field-representative datasets to enhance the effectiveness of plant disease detection is needed. Moupojou et al. presented the FieldPlant dataset that consists of more than 5,000 images taken at the plantations with professional annotations [16]. FieldPlant, in comparison with accepted datasets like PlantVillage or PlantDoc, allows models to be more generalized to natural environments with complicated backgrounds and many leaves per picture, bridging a crucial limit between training AI on in-situ agricultural surveillance. Based on the dataset-based methods, Moupojou et al. introduced a model ensemble framework that uses the Segment Anything Model and Fully Convolutional Data Description to detect several diseases in field images [17]. The system was also able to detect multi-disease by isolating leaf objects and using explainable deep one-class classification to enhance classification accuracy by more than 10% relative to the PlantDoc-trained models and showing the ability of object detection, segmentation and explainable classification to work in a realistic agricultural environment. Balafas et al. in a comprehensive review conducted an investigation on the performance of machine learning and deep learning methods in detecting and classifying plant diseases [18]. The paper classified methods into classification and object detection ones and selected ResNet50, MobileNetV2, and YOLOv5 as models with the best trade-offs between accuracy and computers resources, in particular when deployed on the edges. This highlights the fact that model selection is important in real time agricultural settings.

XAI methods are becoming a part of the pipelines used in plant disease detection. Nigar et al. created a model that uses XAI and can classify 38 different types of plant diseases with high accuracy (99.69%), precision (98.27) and recall (98.26) [19]. This would make the models more transparent, allow farmers to trust them more, and use the data to make decisions and implement timely interventions. Hyperspectral imaging has also become a prospective technology in early detection of diseases. Rayhana et al. surveyed hyperspectral methods of monitoring plant diseases based on their capacity to monitor the disease at the tissue to canopy levels, measure the severity of the disease, and the genetic resistance to the disease [20]. Although hyperspectral methods are expensive and computationally intensive, they are unmatched in terms of sensitivity and can be used to supplement RGB based systems in the accuracy of agriculture. Deep learning models in conjunction with UAV-based remote sensing have also been used to advance the detection of plant diseases. Another technique suggested by Pajany et al. to detect and classify plant diseases using high-resolution UAV images is an Optimal Fuzzy Deep Neural Networks-based Plant Disease Detection and Classification (OFDNN-PDDC) [21]. The model is a combination of a better version of ShuffleNetV2 that can extract features, a fuzzy restricted Boltzmann machine (FRBM) that can identify diseases, and the optimization of the hyperparameters through the Tent Chaotic Salp Swarm Algorithm (TCSSA). Based on experimental findings, 96.18% and 98.85% accuracy on APD and CPD datasets show that it is effective in scalable precision agriculture.

Li et al. conducted the extensive review of deep learning techniques to detect plant diseases, focusing on the benefits of automatizing feature extraction as compared to manual methods [22]. The provided study described the recent tendencies, issues, and prospect of implementing deep learning to detect leaf diseases, and the possibility of more rapid, objective, and scalable methods of applying AI in agriculture. Joseph et al. also tackled the issue of lack of annotated datasets by making real-time datasets of rice, wheat, and maize [23]. Those datasets contained typical fungal and bacterial infections and they trained various deep learning models. The paper recorded high testing precision, the Xception and MobileNet models recorded up to 97.28% in rice and it has shown that training models using domain-specific data enhance disease detection in essential food crops. Bhargava et al. have examined the techniques of computer vision and artificial intelligence-assisted plant disease detection [24]. Their work also put emphasis on deep learning, few-shot learning and soft computing methods in making accurate identifications and diagnoses of an illness with both technical and practical consequences of helping minimize crop loss and making decisions in agricultural fields. Oad et al. proposed an ensemble-based learning method that was combined with explainable AI to detect plant leaf disease [25]. The system was able to test with more than 90 percent accuracy and offer an interpretable analysis of predictions by combining 4 deep learning models (VGG16, VGG19, ResNet101 V2 and inception V3) and explaining them with the help of the LIME. This paper highlights the need to have explainable frameworks to increase the trust and actionable information to farmers. Taken together, the studies show that important progress in the detection of plant diseases using UAV imaging, dataset creation, deep learning, ensemble models, and explainable AI is currently being made. In spite of such innovations, real-time, edge-deployable, multi-crop systems with interpretable outputs are also an open research area that drives the establishment of integrated precision agriculture solutions.

III. PROPOSED SYSTEM

The proposed system is an edge-based wall-based surveillance system that is meant to conduct real-time continuous surveillance of strawberry plants to identify early signs of diseases. Figure.1 shows a proposed work hardware block diagram design. The framework is designed to have a fixed-position IoT camera unit, which is placed at areas of strategic points in the cultivation space and, therefore, covers the area without necessitating mobile inspections.

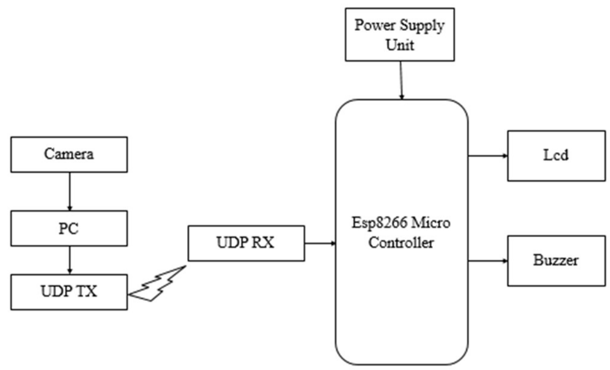

Figure.1 Proposed Hardware Block Diagram

This fixed deployment lowers the complexity of the system besides giving long-term autonomous monitoring. Images of captured plants are transformed locally on an embedded edge computing machine together with a lightweight deep learning model. One of the classifiers is ShuffleNet, which has been chosen as it has low computational complexity and can be used in real-time inference with resource-constrained hardware. The model is conditioned to identify several types of strawberry leaf diseases and healthy plants. Through direct inference on the edge device, the system removes the need to use permanent cloud connectivity, which lessens the latency and saves bandwidth. The system uses a transmission pipeline that is a UDP based one to send detection results to the monitoring interface in order to facilitate fast communication. The protocol reduces delays and facilitates real time feedback that is highly important in time-sensitive agricultural intervention. After a disease is identified, the alert sub system is activated. The alert module is an LCD display which gives a visual status information and an inbuilt buzzer which emits audible warnings.

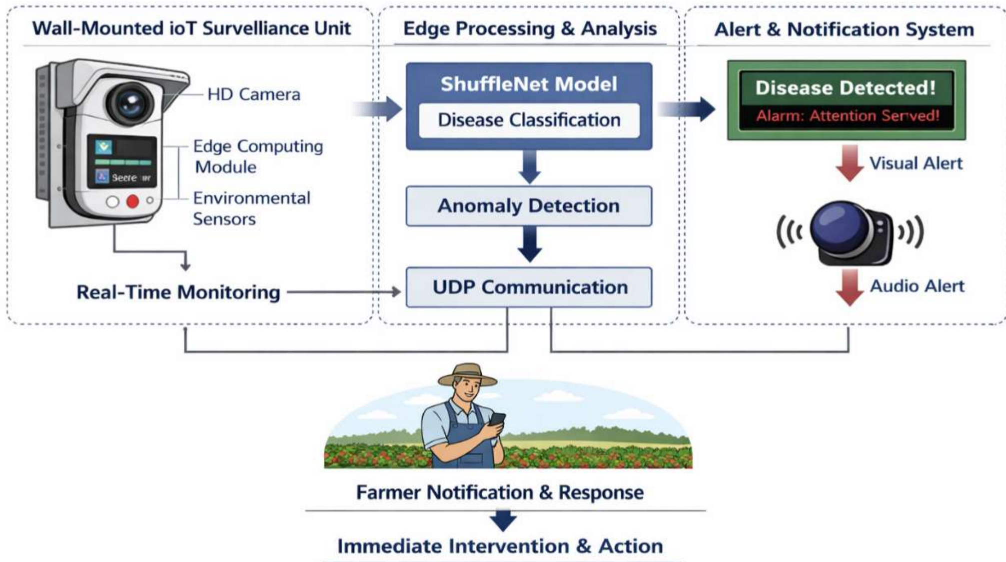

Figure.2 Proposed Work Architecture Diagram

This two-warn system is such that even in cases where the farmers are not at all watching the system, they can promptly react. The whole system is intended to be low energy consuming and stable long time operation in the field environment. Its scalable structure is modular, which means that several wall-mounted units may be used to work on large farms. Figure. 2 shows a proposed work system architecture design. The proposed system is a feasible and cost-effective way to manage agricultural diseases using lightweight deep learning, embedded edge processing, and real-time alert-enabled feedback to manage and control any disease.

IV. METHODOLOGY

The suggested methodology is aimed at developing a real-time strawberry disease detection system, which integrates edge computing, embedded vision, and lightweight deep learning. The system works in a pipelined system that comprises of image capture, pre-processing, disease classification, communication and generation of alerts. Every phase is streamlined so that the latency is low, reliability is high and its application is viable to real world agricultural applications.

A. *Image Acquisition and Edge Surveillance Setup*

An IoT camera module mounted on the wall is fixed at the height and angle to ensure constant monitoring of strawberry plants. Images are consistently captured in the same position with the framing conditions in the stationary configuration, and without motion by the camera, the framing conditions remain constant. To trade of between detection accuracy and power, images are taken at fixed intervals. The surveillance unit will be made to work in the outdoor conditions having a consistent power supply and housing with a weather cover. The constant check-up will enable detection of the signs of the diseases that are not always evident in the course of the periodic manual examination.

The wall-mounted camera continuously captures plant images at fixed time intervals. Let the captured image at time step t be represented as

$$I_t = f_c(S_t, L_t) \qquad (1)$$

where I_t denotes the observed image, S_t represents the visual state of the plant surface, and L_t denotes environmental lighting conditions. The function $f_c(\cdot)$ models the camera capture process, which includes sensor response and lens characteristics. Fixed-position installation ensures that geometric distortion remains constant, enabling stable feature extraction across time.

B. *Image Preprocessing*

Images that are captured are subjected to preprocessing to enhance better classification and eliminate noise. The preprocessing-steps also incorporate the resizing, normalization, and color correction in order to assure the same input-dimensions to the neural network. Adaptive normalization helps to compensate lighting differences created by outdoor conditions partially. This step will guarantee that the model is concerned with disease-relevant visual features including the texture of leaves, discolorations, and spots and not the noise in the environment.

To maintain uniform input for neural inference, the captured image is resized and normalized. Each pixel value is scaled using

$$I'_t(x, y) = \frac{I_t(x, y) - \mu}{\sigma} \qquad (2)$$

where $I'_t(x, y)$ is the normalized pixel intensity at location (x, y), μ is the mean pixel value, and σ is the standard deviation computed over the training dataset. This normalization reduces illumination variance and enhances disease-specific visual patterns such as lesions and discoloration.

C. *Lightweight Deep Learning Classification*

A convolutional neural network that uses ShuffleNet is used in the classification of multi-class strawberry disease. ShuffleNet is chosen because it is effective in making precise inferences with less computational tasks. On the labeled datasets of the strawberry leaf which have healthy and diseased samples, the model is trained. The edge device conducts on-device inference during work, which is able to detect quickly without a connection to the cloud. This is a local processing methodology that minimizes latency and enhances system forbearance in low-connectivity systems.

The preprocessed image is fed into a ShuffleNet classifier optimized for edge deployment. The convolutional feature extraction can be expressed as

$$F_l = \phi(W_l * F_{l-1} + b_l) \qquad (3)$$

where F_l is the feature map at layer l, W_l denotes convolutional weights, b_l is the bias term, and $\phi(\cdot)$ represents the activation function. Channel shuffling improves cross-channel information flow while keeping computation low. The final classification probability for class k is computed using softmax:

$$P_k = \frac{e^{z_k}}{\sum_{i=1}^{K} e^{z_i}} \qquad (4)$$

where z_k is the output logits for class k and K is the total number of disease categories.

D. Real-Time Communication Framework

The output of the detector is sent by a communication protocol based on UDP. UDP is selected because it has a low overhead and the transmission delay is minimal, which is appropriate in the time-critical agricultural monitoring. The communication module maintains that the detection events of disease are directly communicated to the local interface. The design of packets is carried out to avoid congestion and ensures that the system remains responsive at all times.

Once classification is complete, the result is transmitted using a UDP protocol. The packet transmission delay is modeled as

$$T_d = T_p + T_q + T_t \qquad (5)$$

where T_p represents processing time, T_q is queuing delay, and T_t is transmission latency. Minimizing T_d ensures immediate farmer feedback and rapid intervention.

E. Alert and Decision Support Mechanism

After a disease is identified an alert module is triggered to alert the farmer. The interface on the LCD indicates the detected disease type, system status and a built in buzzer sounds warnings. This is a dual-alert system that guarantees that one would be aware even when the operator is not actively monitoring the screen. It aims at enabling quick decision-making and reducing crop losses by intervening on time.

An alert is triggered when the predicted disease probability exceeds a defined threshold θ. The decision rule is

$$A = \begin{cases} 1, & \text{if } \max(P_k) \geq \theta \\ 0, & \text{otherwise} \end{cases} \qquad (6)$$

where A=1 indicates an active disease alert. This mechanism prevents false alarms while maintaining sensitivity to early symptoms.

F. System integration and Scalability

It has a modular and scalable overall architecture. Several wall-mounted units can be installed over extensive cultivation space and linked with a central monitoring location. Edge based processing lowers network traffic and makes distributed intelligence possible. The design enables long time run with low energy usage and therefore it is applicable in precision agriculture applications.

The total system response time is expressed as

$$T_{sys} = T_{cap} + T_{pre} + T_{inf} + T_d \qquad (7)$$

where T_{cap}, T_{pre}, and T_{inf} represent capture, preprocessing, and inference time respectively. Optimizing T_{sys} ensures real-time operation suitable for large-scale agricultural deployment.

V. RESULT & DISCUSSION

The edge-intelligent strawberry disease surveillance system has been tested with the conditions of a real world operation in order to determine the accuracy of classification, latency, energy consumption and the consistency of the system. The multi-class strawberry disease data were experimented with the help of a dataset that is taken in natural field settings. The testing is based on real performance of the deployment and not just laboratory tests.

A. Classification Performance

The ShuffleNet-based classifier was applied to various categories of disease such as healthy leaf, leaf scorch, powdery mildew and bacterial spot. Table I is a summary of the classification obtained using the experimental data.

TABLE I. DISEASE CLASSIFICATION PERFORMANCE

Class Label	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Healthy Leaf	97.2	96.8	97.0	96.9
Leaf Scorch	95.8	96.1	95.9	95.7
Powdery Mildew	96.4	95.6	96.0	95.8
Bacterial Spot	94.9	95.3	95.1	95.0
Overall	96.1	95.9	96.0	95.9

The classifier is also consistent between classes of diseases, which means that it can extract the same features with different lighting conditions. Balanced precision and recall are verified by the high F1-score and are valuable to reduce false alarms and false detection.

B. Latency and Real-Time Performance

The aspect of real-time responsiveness is important in the intervention of diseases in the early stages. The overall processing latency was taken as an average of 1,000 inferences in a single image.

TABLE II. SYSTEM LATENCY MEASUREMENT

Processing Stage	Average Time (ms)
Image Capture	18
Preprocessing	11
Model Inference	27
Communication Delay	9
Total Response	65 ms

The system has confirmed that it can meet real-time requirements as the total response time is 65 ms. Table II shows a latency of the system performance. Edge inference removes the cloud round trip delay, hence the architecture is acceptable in agricultural time sensitive monitoring.

Figure 3 shows the distribution of the latency of processing phases. It is visible that, the neural inference takes the biggest portion of the computation, but is lightweight enough to be deployed as an embedded system.

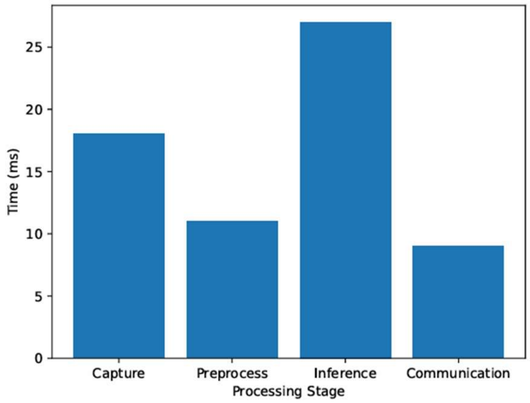

Figure 3.Processing Latency Distribution

The latency in communication is very short because of the UDP based protocol. Bar chart of time allocation in capture, preprocessing, inference, and communication

C. *Energy Consumption Analysis.*

Constant operation in fields requires energy efficiency. Active monitoring measured the power-use. Table III shows an energy consumption comparison.

TABLE III. ENERGY CONSUMPTION COMPARISON

Mode of Operation	Power Usage (W)
Idle Monitoring	2.8
Active Inference	4.1
Alert Activation	4.5

Even in the process of active classification, the system is low energy consuming. The insignificant rise in the process of alert activation proves that embedded alarms do not severely affect the power stability.

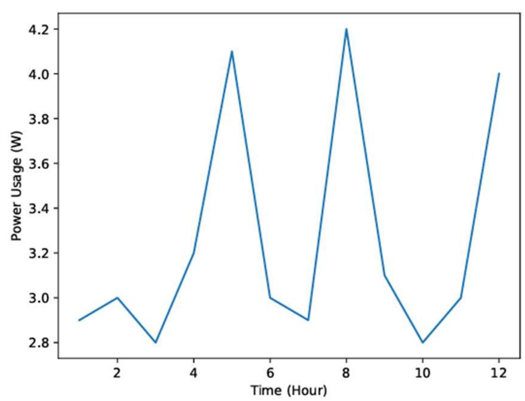

Figure 4. Energy Consumption Over 12 Hours

A line graph of energy consumption during 12 hours of monitoring is given in Figure 4. The system can be used in long-duration operation due to the stability of the consumption with small spikes on the occasions of detection.

D. *Detection Reliability in Field Conditions*

The system was implemented in semi-controlled outdoor setting so that it could run continuously during 7 days. Detection reliability was determined by the successful classification in case of variation of light and incomplete superimposition.

TABLE IV. FIELD DEPLOYMENT RELIABILITY

Condition Tested	Detection Success (%)
Morning sunlight	96.5
Afternoon glare	94.7
Cloudy environment	96.2
Partial leaf overlap	93.9

Findings indicate in table IV that it has good resistance to environmental changes. Minor decrease in performance during glare conditions will be anticipated but it will be within acceptable agricultural use limits.

E. *Discussion*

Through the experimental analysis, the suggested edge-intelligent surveillance system is proven to offer an achievable trade-off of accuracy, speed and energy efficiency to real-time agricultural surveillance. The ShuffleNet-based classifier has good detection rates and can be run on the computational resources of embedded systems, which proves it to be suitable in terms of the edge deployment. On-device inference and UDP communication can provide low latency to relay instant feedback required in early disease intervention. Field test also reveals that the system is stable in changing environmental conditions such as changes of light as well as partial occlusions. Though slight decrease in the performance was noticed in the extreme glare conditions, the detection rate was not beyond the acceptable operating range. The fixed wall mounted design helps to achieve a consistent image capture and it is simpler to install in large farms. In sum, the findings suggest that a lightweight edge intelligence may be a viable substitute to a manual examination and cloud-based monitoring systems and provide a scalable and affordable solution to precision agriculture.

VI. CONCLUSION

In this paper, an edge-intelligent IoT-based monitoring surveillance system was introduced to detect real-time strawberry disease based on walls. The experimental results validate the following: the proposed framework has high classification accuracy, low latency and energy consumption, and it can be applicable to constant field deployment. The system avoids use of the cloud infrastructure and provides instant disease alerts by combining a lightweight ShuffleNet model with an embedded edge processing. The fixed surveillance system offers uniform surveillance and allows early diagnosis of symptoms, which is a vital measure to reduce losses on crops. This work has made a major contribution in the smooth integration of edge computing, lightweight deep learning, and real-time alert systems into a scalable agricultural monitoring system. The findings indicate that it is possible to construct practical smart farming solutions based on relatively inexpensive hardware and without compromising their performance. Field tests indicate that the design can be operated reliably and continuously even with the diverse environmental settings. The further development of the work will be aimed at the further extension of the data set covering more disease categories and seasonal differences. Decision support could be further improved by integrating it with predictive analytics and automated recommendations on treatment. Multi-node scale deployment and solar power will be also investigated to provide the sustainability of precision farming.

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