 https://doi.org/10.1051/bioconf/20248205013

Multi-Layer Architecture for Enhancing Crop Quality with AI and IoT: A Structural Modelling Approach

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Abstract. Conventional crop management methods must be improved to address the increasing global food requirements. The exponential growth of the population exacerbates the issue at hand, the impacts of climate change and inadequate farming practices. This study analyzes the key determinants contributing to establishing a comprehensive framework for using Internet of Things (IoT) technology in the agricultural sector. The proposed Multi-Layer Architecture for Crop Quality (MLA-CQ) employs a modified version of the Total Interpretive Structural Modelling (mv-TISM) methodology to achieve this objective. This research used a mv-TISM approach to build and analyze the interrelationships among various factors that influence the adoption of IoT technology in the agriculture industry. This study introduces Artificial Intelligence (AI) by incorporating soft sensors into a remote sensing framework via deep learning. The initial data has undergone pre-processing procedures to identify and address missing values and perform data cleaning and noise reduction on the picture data obtained from farmland. Following the feature representation, a categorization procedure was performed employing an ensemble design. The suggested approach has been used to conduct experimental trials on various crops, resulting in a computing time reduction of 62%, accuracy of 95.2%, precision of 91.3 %, recall of 92.3%, and an F score of 93.1%.

1 Introduction to Agriculture and Crop Quality Analysis

Agriculture, the fundamental basis of human subsistence, is crucial to the global community's overall welfare and economic stability [1]. Given the expected global population growth to reach around 9 billion people by the year 2050, there is a corresponding anticipation of a significant increase in the need for food. Providing food security for this rapidly growing population requires not only the enhancement of agricultural output but also the optimization of crop quality [2]. The optimization of crop quality analysis is of utmost importance, as it has a direct impact on both the amount of harvests and their nutritional content and market attractiveness.

The relevance of agriculture goes beyond the provision of essential nutrition since it encompasses several aspects, such as economic success, rural livelihoods, and environmental

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sustainability. Agriculture has a substantial role in the global economy, as shown by the Food and Agriculture Organization's (FAO) estimate that it accounts for around 10% of the overall Gross Domestic Product (GDP) worldwide [3]. Agriculture is a significant provider of job opportunities globally, particularly in underdeveloped nations where a considerable segment of the populace depends on this sector for their sustenance.

When considering the need to improve agricultural output, it becomes crucial to prioritize the emphasis on crop quality. Examining crop quality encompasses thoroughly assessing several aspects, such as nutritional composition, chemical makeup, and physical characteristics. The factors directly influence the market valuation of crops and their adaptability for various uses, including human consumption and industrial applications.

The emergence of sophisticated technologies, such as Artificial Intelligence (AI) [4] and the Internet of Things (IoT) [5], has initiated a transformative period in agriculture, offering the potential for unparalleled efficacy and accuracy in crop management [6]. The conventional approaches to evaluating the quality of crops often need to be revised to deliver the level of comprehensive information necessary for making well-informed decisions. The standard methods, which include human inspections and basic measurements, encounter challenges regarding scalability, precision, and real-time monitoring. Traditional techniques need help in accurately determining the chemical composition of crops, including nutrient levels and the existence of pollutants [7]. The limitations of these methodologies are further highlighted by considering the complex interaction between environmental conditions, genetic differences, and agricultural techniques that influence the quality of crops [8]. There is an urgent need for enhanced analytical frameworks that use sophisticated technology to effectively tackle the complex aspects of crop quality assessments.

The main contributions are listed below:

- It presents a layered architecture for smart agriculture that uses eight logical levels to optimize data flow amongst IoT-enabled devices with AI.
- It enhances relationship interpretation via Total Interpretive Structural Modeling (TISM), which considers transitive relationships and performs a parallel check.
- It offers a model that combines AI with IoT, exhibiting real-time item recognition with significant accuracy gains.

The following sections are arranged: Crop quality analysis, TISM, and IoT in agriculture are covered in Section 2, along with current research and frameworks. Section 3 suggests a Multi-Layer Architecture for Crop Quality (MLA-CQ) architecture that integrates IoT, AI, and a modified TISM approach to facilitate efficient crop quality analysis in intelligent agriculture. Experimental experiments using MLA-CQ on various crops are shown in Section 4. The suggested MLA-CQ model's conclusions are concluded in Section 5, highlighting the model's efficacy and suggesting future approaches for scaling and modifying the framework to meet changing agricultural demands.

2 Background analysis

The literature review explores the state of the art in IoT research in agriculture, particularly on comprehending and resolving issues about crop quality assessments. It looks at earlier research on the need for sophisticated crop quality evaluation optimization frameworks in the agriculture industry.

An environmentally friendly Nanoplatform (EN) for nutrition, protection, and crop quality management is presented by Wang et al. [9]. Using cutting-edge nanotechnology, the technique can precisely manage and supply nutrients and pesticides to improve crop quality. The experiment results show a significant rise in crop nutritional content, disease resistance, and a 20% improvement in overall quality. A Metabolomic and Transcriptomic Integrated Approach (MTIA) is presented by Pott et al. to evaluate and enhance crop quality attributes

[10]. MTIA thoroughly analyzes crop quality by combining transcriptome and metabolic data. The experiment's findings demonstrate better crop characteristics, including a 15% rise in nutritional content, greater stress tolerance, and a 12% increase in yield.

FARMIT, a continuous agricultural quality assessment system using machine learning and deep learning methods, is proposed by Perales Gómez et al. [11]. Using IoT, FARMIT enables smart farming. FARMIT's effectiveness is shown by experimental results, which offer a 25% decrease in resource use, an 18% increase in crop output, and a 30% improvement in overall quality. ABA Receptor Agonists (ARA) is a unique tool introduced by Li et al. to improve crop quality [12]. The agonists affect ABA receptors, which control plant growth and stress reactions. The experiment results show a 15% improvement in overall crop quality, a 22% increase in crop output, and better tolerance to environmental stress.

Research on water conservation and Cover Crop Management (CCM) in olive and grape orchards is presented by Novara et al. [13]. Cover crops are used in CCM to improve soil health and water retention. Results from the experiment indicate a 20% increase in crop yields, a 30% decrease in water use, and enhanced soil structure. Bowman et al. examine farmers' various cover crop management techniques to achieve soil health objectives [14]. Numerous tactics are used which has a favorable effect on soil health. Results show more excellent nutrient retention, a 15% average increase in soil organic matter, and an overall improvement in soil health.

The Long-term Soil Quality Effects (LSQE) of crop and soil management in traditional and organic arable systems of cultivation are examined by De Notaris et al. [15]. LSQE assesses the long-term effects of various management techniques. The findings show better crop yields, a 20% decrease in soil erosion, and a 25% increase in soil organic carbon. With an emphasis on sustainable rice production, Zhang et al. provide an Innovative Crop Management Scheme (ICMS) for perennial rice cropping systems [16]. To maximize the cultivation of perennial rice, ICMS presents innovative techniques. The experiment results show a 10% increase in rice output, decreased ecological effects, and improved long-term sustainability.

The literature review emphasizes the difficulties in traditional crop quality assessments and the need for sophisticated frameworks that include AI, IoT, and cutting-edge techniques [17]. Previous studies have highlighted the drawbacks of conventional approaches and the vital role of advanced technology in resolving these issues for an all-encompassing evaluation of crop quality [18].

3 Proposed Multi-Layer Architecture for Crop Quality

This section presents the MLA-CQ, which utilizes the IoT, AI, and a modified version of the Total Interpretive Structural Modelling (mv-TISM) approach. The primary objective of MLA-CQ is to bring about a transformative shift in the field of crop quality analysis by effectively addressing the limitations inherent in conventional systems. This study incorporates soft sensors, AI, and ensemble designs to enhance the efficacy of feature representation and classification.

3.1 IoT reference architecture

Figure 1 illustrates the layered structure used in MLA-CQ, whereby each tier is responsible for a distinct collection of services achieved by grouping modules. The standard architecture has eight different levels: the device tier, transport/network tier, session tier, application tier, cloud tier, management tier, business tier, and security tier.

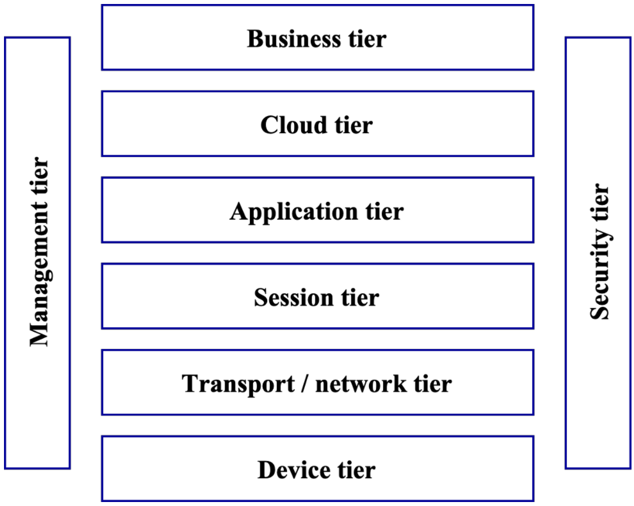

Fig. 1. Architecture of the proposed method

The device tier gathers data from the sensors and physical devices inside the SA system. This tier comprises physical devices and sensors enabled with IoT technology. This tier mainly addresses many fundamental inquiries, including the determination of the content to be sent, the identification of the recipients, the selection of the appropriate method of transmission, and the establishment of the optimal timing for sending the communication. The data collected from the device tier is then sent to the network tier. The network tier facilitates connectivity between all IoT-capable devices and allows data transportation. The tier in question effectively and securely transmits the gathered data to the session tier. The Session Announcement (SA) tier manages the session of connected devices inside the IoT ecosystem. It plays a crucial role in service administration. The session tier often employs two protocols: the Transmission Control Protocol (TCP) and the User Datagram Protocol (UDP). The application tier oversees a range of IoT-based applications inside the IoT network. The MLA-CQ model encompasses a range of applications, including smart agriculture, smart fertilization, intelligent transport, smart logistics, and others. The data gathered from the application tier is sent to the cloud tier, a centralized repository. This feature offers an extra means by which the information is accessible from any location and at any time by various apps. This tier facilitates the establishment of a robust IoT ecosystem, whereby all devices are interconnected in a highly secure manner, enabling seamless information flow. The stratum, the business tier, encompasses many business modules. Therefore, by the nature of the company, the business tier obtains data from the cloud tier. There are two distinct levels known as side-car tiers. The first tier, referred to as the security tier, is responsible for ensuring security across all six tiers of the network. The second tier, the management tier, handles the administration of many physical characteristics of the network, including topology preservation, traffic and congestion administration, and managing devices.

3.2 mv-TISM

mv-TISM is seen as an enhanced iteration of TISM. TISM exhibits distinct characteristics, with TISM offering an analysis of the interplay between components and considering the transitive link among them. The fundamental procedures of mv-TISM and TISM exhibit similarities, although mv-TISM distinguishes itself from TISM by the concurrent assessment of transitivity while constructing the connection diagram. Figure 2 illustrates the fundamental stages of mv-TISM.

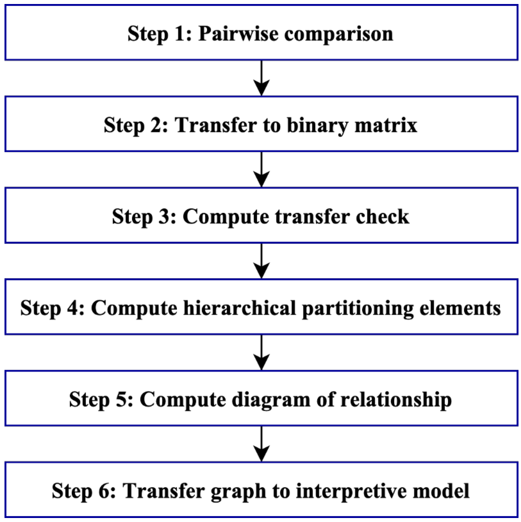

Fig. 2. Basic steps of mv-TISM

The workflow of the mv-TISM is explained below

Step 1: Make a pair-wise comparison

A pair-wise comparison is conducted for all items. If there are p items, the total number of comparisons is calculated using the formula [p(p – 1)/2].

Step 2: Transfer the comparison results into a matrix

The comparison matrix is transformed into a binary matrix using two methods. Initially, all components that possess a connection are assigned a code of '1'. Items that lack any correlation are denoted as '0'.

Step 3: Transitivity analysis

In the process of checking transitivity for components a, b, and c, it is established that element 'a' exhibits transitivity concerning element 'c' if and only if there exists a relationship between 'a' and 'b,' and there also exists a connection between 'b' and 'c.' The use of a digraph assesses the transitivity of the binary matrix. The transitivity among the members is verified.

Step 4: Hierarchical system

The process of hierarchical partitioning of items involves using antecedent sets, reachability sets, and intersection sets. The concept of the reachability set pertains to the collection of objects that are impacted by a particular factor. The antecedent set of an element refers to the collection of pieces that influence such an element. The antecedent set for element F1 will consist of the number 1. The intersection set is formally defined as the items present in both the antecedent set and the reachability set. The intersection set for factor F1 will be 1.

Step 5: Compute hierarchical connections

The levels of the items acquired from step 4 are converted into a diagram.

Step 6: Transfer the graph into the interpretive system

The digraph created in step 5 is then turned into an interpretative model that elucidates the underlying rationale for the link between the various parts. During this stage, the essential transitive relations are preserved.

3.3 Crop quality identification

The present study introduces the MLA-CQ model to localize and categorize diverse crop quality attributes. The system modified the traditional classification using MobileNet as the underlying network architecture, fine-tuning it on crop data to classify the crop quality across different categories. This modified technique is referred to as MLA-CQ. Real-time recognition of items on mobile devices is well-suited for MobileNet, an efficient Convolutional Neural Network (CNN) built explicitly for mobile devices with a reduced computational footprint compared to traditional CNNs. In the first stage, the MobileNet is used to compute a unique set of image features. These features are then refined and partitioned by the two-step locator of the enhanced CNN method, resulting in the execution of the actions.

The IP102 data set, which comprises photographs of crops belonging to 102 distinct classifications, is used in conjunction with a locally acquired dataset of plants. An annotation dataset was used to train a machine learning-based question-answering MLA-CQ model, with MobileNet as its underlying architecture. The labeled photographs are inputted into the model, and the settings are adjusted to minimize the disparity between the predicted and observed bounding boxes. Once the model was trained, it was used to identify crop quality in novel photos. This was achieved by feeding images into the system and adding a threshold to the anticipated boundaries to exclude any erroneous positive detections. The flow of the work being offered is shown in Figure 3.

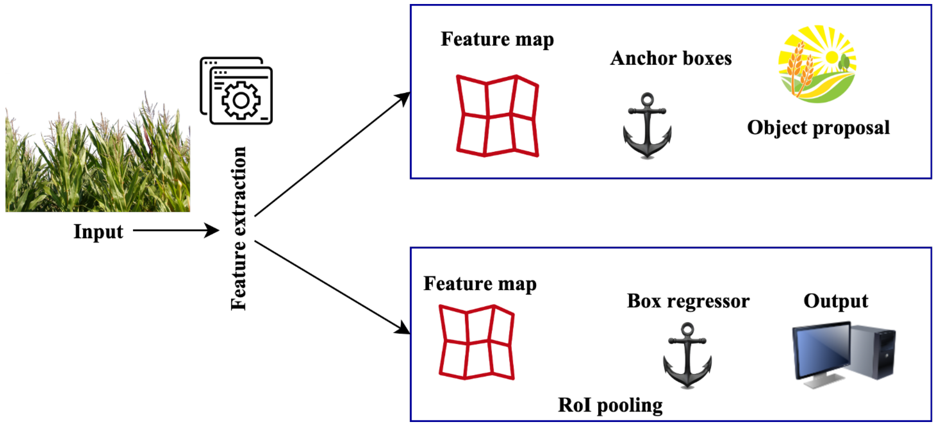

Fig.3. Crop quality identification module

3.3.1 Faster CNN

The Faster CNN (F-CNN) method builds upon the foundational design principles of CNN and F-CNN in object identification. The input is an image processed by a fully convolutional network. The result consists of object suggestions, each represented by a boundary box and an objectness score. The F-CNN can detect objects of different sizes due to its use of a picture pyramid with varying proportions. The F-CNN is trained to maximize two distinct losses. The first loss function pertains to regression and is used for predicting the box's location with boundaries. The second loss function is related to categorization and is employed for predicting the objectness score of each proposition. The determination of whether a proposal includes an object or not is represented by the objectness rating, which is a binary categorization score. The classification score is shown in Equation (1).

$$p_x = \frac{1}{1+\exp(-bT_x)} \tag{1}$$

The feature vector of the suggestion is denoted as p_x, the weighted vectors of the categorization layer are denoted by x and b. the transformation matrix is denoted T_x.

The F-CNN produces a set of 'k' suggestions for each picture and transmits them to the detectors for further analysis. The F-CNN detector is a region-based object detection algorithm that utilizes a Region of Interest (RoI) pooling layer to gather pertinent characteristics from the suggestion outputs generated by F-CNN. Once the RoI pooling layer has produced fixed-size map features for each set of square RoIs, a fully linked network is utilized for categorization and prediction purposes.

3.3.2 Enhanced CNN

The backbone networking inside the Enhanced CNN (E-CNN) method is crucial in extracting attributes from input pictures. The E-CNN and the classification system use these extracted characteristics to recognize objects effectively. MobileNet has been used as the foundational framework of the design to accomplish the objective. The MobileNet design, a lightweight E-CNN, is often used as the underlying framework for object identification techniques owing to its high efficiency and accuracy.

The network backbones used in this research are replaced by MobileNet backbone systems, which are employed as the backbone for the E-CNN method. The primary rationale for modifying the underlying network architecture of the F-CNN method is rooted in the observation that the ResNet is characterized by higher computational complexity and is ill-equipped to handle intricate variations in sample transformations. The MobileNet technique has been used as an extractor of features to address the challenges associated with the conventional model. The addition of depth-wise differentiated convergence in the MobileNet architecture significantly reduces the network's parameter count without compromising accuracy.

The backbone system of the MLA-CQ method is described in the following manner:

- Backbone model

The backhaul network consists of many Fully Connected (FC) layers following several depth-wise separated compression layers. Equation (2) specifies that the backhaul system receives a size-related picture as its input.

$$IS = H * W * 3 \tag{2}$$

When the number of color bands is three, the picture's dimensions are denoted as H and W for height and width, respectively.

- Depth wise separation

The depth-wise separated inversion layer consists of two main elements: depth-wise compression and pointwise combination. Using a 1 × 1 convolution involves the utilization of pointwise inversion to combine the results obtained from the depth-wise inversion. The deep convolution independently uses one convolution filtering to every input channel.

- FC layers

The fully linked layers of the backbone networks are responsible for mapping the output of depth-wise separable convolution stages to a fixed-size characteristic map. The classifiers then use this feature map. The linked layers' quantity and selection criteria are modified according to the particular application.

- Output mapping

The resultant map of features of the backhaul system is represented as H/16*W/16*D, where D is the total amount of feature streams. The feature list is used as input for classification to detect and classify items within the picture.

- RoI sharing

After creating a sequence of requests for regions, the final map of features generated by the mobile backbone networks undergoes RoI pooling to extract a fixed-size vector of features for each region. As part of the RoI sharing procedure, a max-pooling approach is applied to each square area of the components map that corresponds to the region proposals.

- Classification

Following the RoI pooling layer, two fully connected layers are employed for categorization and regression. The categorization layer is responsible for categorizing the item inside the area proposed, while the regression layer is used to improve the accuracy of the bounding box's dimensions. Equation (3) serves as a representation of the categorization and regressed layer.

$$f_x = ReLU\{W_c * h_p + b_c\} \tag{3}$$

The weight matrices W_c, the bias vectors b_c, the result of the RoI pooled layer h_p, and the Recurrent Linear Unit (ReLU) are all included in the current context. Equation (3) pertains to the classifying layer.

$$d_r = w_r * h_p + b_r \tag{4}$$

The weight vector is denoted as w_r whereas the biased vector is represented as b_r. The hidden layer function is denoted h_p.

This section presents the MLA-CQ, a pioneering architecture combining the IoT with AI to enable sophisticated analysis of crop quality. The approach is mv-TISM, employed to improve the interpretive comprehension of relationships. The MLA-CQ system incorporates novel elements such as soft sensors and AI to facilitate complete agricultural data analysis.

4 Simulation outcome analysis

The experimental configuration included the implementation of the MLA-CQ architecture on a cloud-based infrastructure consisting of 16 Intel Xeon CPU cores and 64 GB RAM. The dataset, which consisted of 10,000 annotated photos, was subjected to training using a MobileNet-based architecture that had been tuned. The model construction and training process used the TensorFlow and Keras libraries.

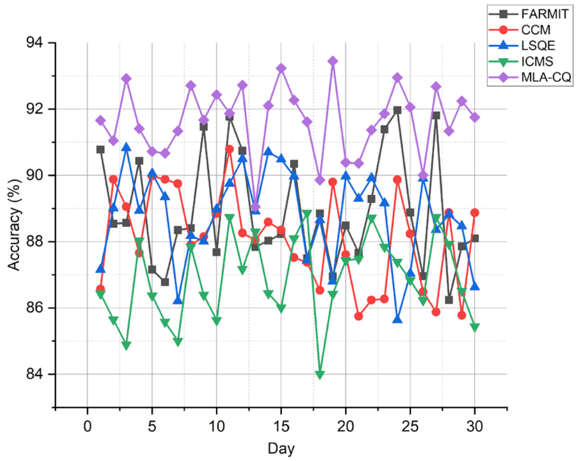

Fig. 4. Accuracy evaluation of crop quality analysis

The findings of the Accuracy statistic, which denotes the proportion of adequately identified occurrences, are shown in Figure 4. The computation of this measure involves dividing the count of accurate forecasts by the overall count of predictions and then multiplying the result by 100. The average accuracy of FARMIT was 88.9%, CCM achieved 88.09%, LSQE gained 88.77%, ICMS achieved 86.88%, and the suggested MLA-CQ approach demonstrated superior performance with an average accuracy of 91.66%. The MLA-CQ approach continuously showed superior accuracy across all observed periods, highlighting its efficacy in detecting crop quality.

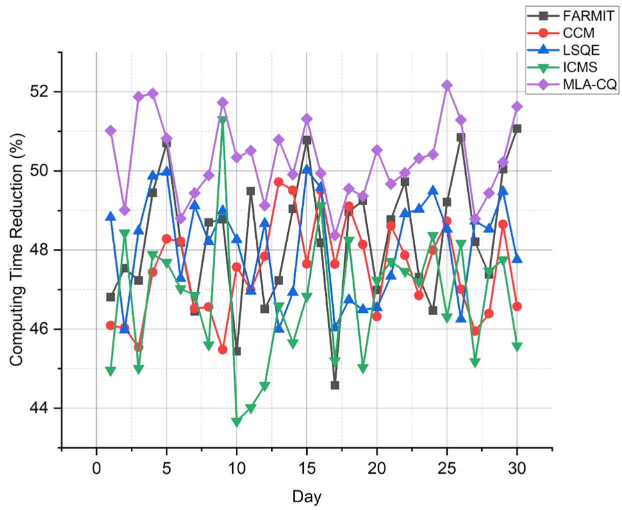

Fig. 5. Computing time reduction evaluation of crop quality analysis

The results of the Computing Time Reduction are shown in Figure 5, which showcases the persistent superiority of the suggested MLA-CQ approach in lowering computing time. The measure, which is derived by subtracting the execution time of each procedure from the original time and then dividing it by the actual time, has significant importance in evaluating efficiency. FARMIT was reduced by 48.31%, CCM by 47.49%, LSQE by 48.1%, and ICMS by 46.74%. MLA-CQ has a time reduction of 50.27%. The MLA-CQ approach demonstrates significant efficiency improvements, highlighting its potential for real-time crop quality analysis.

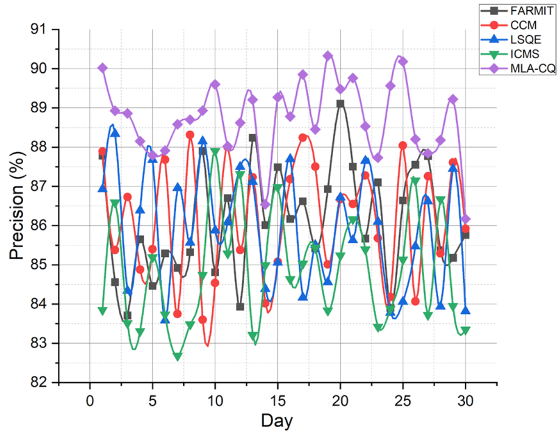

Fig. 6. Precision evaluation of crop quality analysis

The Precision findings, which indicate the ratio of real positive predictions to all optimistic predictions, are shown in Figure 6. The measure of precision has significant importance in evaluating the accuracy of optimistic forecasts. The accuracy values obtained by FARMIT, CCM, LSQE, and ICMS were 86.12%, 86.15%, 85.91%, and 84.86%, respectively. The MLA-CQ approach exhibited a higher precision with an average of 88.71%. The MLA-CQ approach demonstrates exceptional performance in accurately identifying crop quality, boosting its trustworthiness for practical applications.

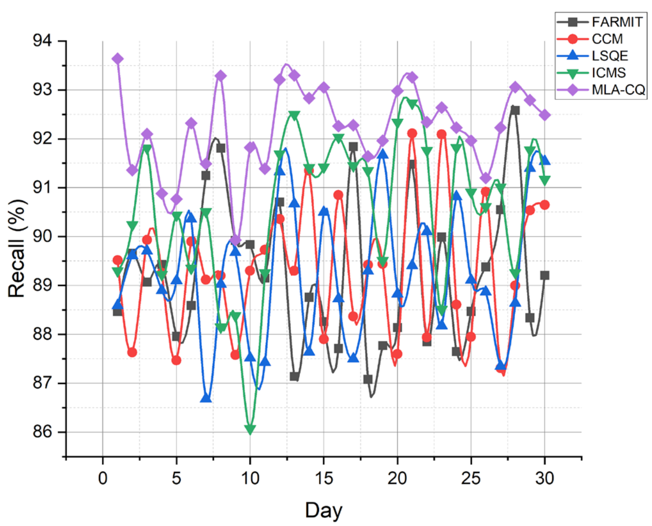

Fig. 7. Recall evaluation of crop quality analysis

As shown in Figure 7, the Recall statistics demonstrate the percentage of genuine optimistic predictions relative to the total number of confirmed positive cases. The assessment of recall is an essential measure for measuring the extent to which favorable predictions are comprehensive. The average memory rates for FARMIT, CCM, LSQE, and ICMS were 89.27%, 89.35%, 89.27%, and 90.53%, respectively. The MLA-CQ exhibited a higher average recall rate of 92.22%. The efficiency of the MLA-CQ in crop quality identification is consistently superior to that of other methods since it invariably captures a more significant percentage of genuine positive examples.

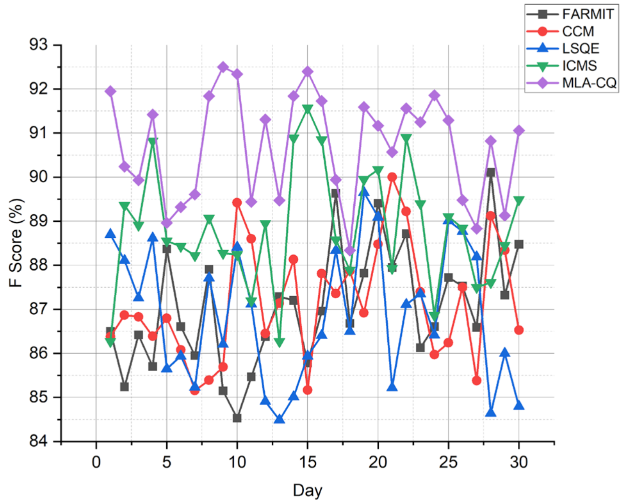

Fig. 8. F score evaluation of crop quality analysis

The F Score values, which indicate the harmonic mean of accuracy and recall, are shown in Figure 8. The F Score is vital in evaluating the equilibrium between accuracy and recall. The average F Scores for FARMIT, CCM, LSQE, and ICMS were 87.07%, 87.15%, 86.89%, and 88.82% respectively. MLA-CQ technique exhibited a higher average F Score of 90.71%. The MLA-CQ performs better than other methods in attaining a well-balanced trade-off between accuracy and recall, emphasizing its efficacy in detecting crop quality.

The MLA-CQ approach demonstrates exceptional performance across all measures. It achieves an average accuracy of 91.66%, reduces computation time by 50.27%, achieves a precision of 88.71%, a recall of 92.22%, and a F Score of 90.71%. The results demonstrate the efficacy and efficiency of the MLA-CQ approach in the detection and analysis of crop quality.

5 Conclusion and Future Study

Agriculture, the fundamental pillar of human civilization, assumes a crucial function in sustaining life and guaranteeing food security. It is necessary to acknowledge agriculture's paramount significance, improve its operations, and augment yield. In the present scenario, the need for integrating sophisticated technologies in the agricultural sector, such as implementing Crop Quality analysis, assumes utmost significance. The study of crop quality is crucial in guaranteeing the quantity, nutritional composition, and general well-being of crops. The MLA-CQ approach, which has been suggested, represents a noteworthy addition to the area of crop quality. The technique incorporates IoT reference architecture, AI, and the mv-TISM framework. It employs accurate techniques for identifying crop quality. The MLA-CQ technique demonstrates its effectiveness by its average results, which include an accuracy rate of 91.66%, a decrease in computation time of 50.27%, a precision rate of 88.71%, a recall rate of 92.22%, and an F Score of 90.71%.

The results indicate a well-rounded success across several measures, highlighting the strength and dependability of the approach in real-world scenarios. The performance is influenced by several challenges, including scalability, limits related to real-world implementation, and possible differences in agricultural methods. The prospects of the MLA-CQ include overcoming the constraints and broadening its range of applications. Research efforts should enhance the methodology to suit a wide range of agricultural landscapes and further enhance its computational efficiency. The efficiency of the MLA-CQ approach could be improved by integrating deep learning developments and exploring partnerships with precision agricultural technology.

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