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A multi-tier framework of decentralized computing environment for precision agriculture (DCEPA)

Kiran Muniswamy Panduranga[1], Roopashree Hejjaji Ranganathasharma[2]
[1]Department of Computer Science and Engineering, Government Engineering College, Hassan,
Affiliated to Visvesvaraya Technological University, Belagavi, India
[2]Department of Artificial Intelligence and Data Science, GSSS Institute of Engineering and Technology for Women, Mysuru,
Affiliated to Visvesvaraya Technological University, Belagavi, India

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ABSTRACT

Although collecting enormous volumes of heterogeneous data from many sensors and guaranteeing real-time decision-making are problems, precision agriculture (PA) has emerged as a promising approach to increase agricultural efficiency. The efficacy of current centralized solutions is limited in large-scale agricultural settings due to resource limitations and data saturation. In order to solve these problems, this paper suggests a decentralized computing environment for precision agriculture (DECPA), which divides resource management and data processing among several layers (end, edge, and cloud). DECPA optimizes task execution and resource allocation in the field by utilizing ensemble machine learning models (deep neural network (DNN), long short-term memory (LSTM), autoencoder (AE), and support vector machine (SVM)) and a multi-tier architecture. The findings demonstrate that DECPA combined with DNN performs better than alternative models, achieving a 20% decrease in energy usage, an 18% speedup in response time, a 5% improvement in accuracy, and a 51% reduction in latency. This illustrates the system's capacity to manage massive amounts of data effectively while preserving peak performance. To sum up, DECPA uses decentralized resources and cutting-edge machine learning models to provide a scalable and affordable precision agriculture solution. To improve the system's flexibility and real-time responsiveness, future research will investigate additional optimization and use in various agricultural contexts.

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Corresponding Author:

Kiran Muniswamy Panduranga
Department of Computer Science and Engineering, Government Engineering College
Hassan, Affiliated to Visvesvaraya Technological University
Belagavi- 590018, Karnataka, India
Email: mtech.kiran@gmail.com

1. INTRODUCTION

The area of precision agriculture (PA) calls for adopting various advanced technologies that can be used for autonomous management of farming region [1]. The primary goal of PA is towards optimizing various specific resources (pesticides, seeds, fertilizers, and water) adopted in any standard agricultural practices with an intention towards improving efficiency in farming, minimizing environmental impact, and enhancing yield of crops [2]. Various key components in PA are sensors and internet-of-things (IoT), usage of geospatial technology, drones and aerial imaging, data analytics, automated equipments (e.g. machinaries, harversters, and tractors), and variable rate technology [3]-[8]. There is an increasing attention of PA among scientific community which can be attributed by positive rationale e.g. sustainability, resource efficiency, increased yield, and data-driven decision. However, PA is also characterized by various challenges too. The initial challenge is that PA involves higher initial cost which is mainly due to inclusion of various devices and technology that also demands specific way of configuring and maintaining for long-term operation. PA is also characterized by voluminous yield of agricultural data from various sensing devices while such massively generated data also demands a proper way to integrate them. Owing to inclusion of heterogeneous forms of devices, the complexity of integrating such data arises exponentially. From the viewpoint of infrastructure and connectivity, usually farming area are located remotely where better signal quality cannot be anticipated much. This acts as main obstacle towards implementing smart farming operations. The other challenges are data privacy and security [9] and environmental factors [10]. Such challenges are analyzed to be well-addressed by adopting machine learning approaches [11]-[13]. Exercising machine learning approaches on field data can offer predictive analysis of yield, weather, disease in crops. Deep learning is already investigated by various researchers towards predicting nutrient deficiency, pest infestation, disease by analyzing images of farming region [14]. However, existing research work using deep learning is often found to be more inclined towards accomplishing higher accuracy while the extensive computational and resource cost is often ignored.

However, machine learning models also encounters various rounds of on-going practical issues. The first issue is related to poor data availability and sub-optimal quality of it which is mainly due to increased cost associated with data collection. Adoption of PA also calls for adopting multiple devices and technologies which further give rise to diversified data that are quite challenging to analyze in real-time owing to lack of standardization. Another critical problem is that existing studies using machine learning models have mainly focused on use-case of crops or specific farming aspect without considering varying condition associated with it. Such modelling may suit well for standalone problem addressing but its lack of generalization leads to narrowed scope of applicability to other set of problems. Hence, they are not cost-effective when it comes to practical world deployment. Further, machine learning models are build on trained data with specific range of features which will work well when they are validated with similar set of untrained data; however, the problem shoots up when they are exposed to diversified climatic condition on unforeseen variables. This phenomenon leads to outliers eventually. Still, after all these shortcomings, machine learning is always a better and cost-effective choice to implement a proactive solution for improving the overall performance of PA. It is because of the reason that different variants of machine learning exists while they are still in nascent stages to be investigated. With its power to realize the complex pattern of problems, machine learning still offer a better choice to understand the problem.

Various related work has been studied in perspective of machine learning adoption to understand their effectiveness. The adoption of long short-term memory (LSTM) has been presented by Gafurov *et al.* [15] in order to perform predictive analysis of crop recognition in PA. Bhimavarapu *et al.* [16] have presented a predictive model when LSTM is used for optimizing predictive performance towards crop yield rate. Similar direction towards predictive performance optimization is also carried out by Shen *et al.* [17] where random forest (RF) is jointly used with LSTM towards analyzing growth rate of crops. Another version of deep learning model known as autoencoder (AE) is implemented by Mujkic *et al.* [18] in order to understand the degree of anomalies followed by positively confirming them for agricultural vehicles. Iatrou *et al.* [19] have developed a predictive model towards realizing nitrogen demands using variational AE where transformed data representation is learned to extract feature followed by anomaly detection. Bai et al. [20] have presented discussion of the AE with stacked structure inclusive of encoder and decoder in order to categorize the images obtained from remote sensing devices. Al-Naeem *et al.* [21] have used support vector machine (SVM) in order to perform monitoring of the crops by controlling the movement and location of unmanned aerial vehicle (UAV). Adoption of SVM is also witnessed to address the classification problems of stress-related traits among plants as noticed in work presented by Islam *et al.* [22]. Lyu *et al.* [23] have used gaussian Naïve Bayes (GNB) classification approach for estimating the center line of agriculture area. Adoption of deep neural network (DNN) has been also witnessed in existing literatures of PA. Jin *et al.* [24] have constructed a predictor using DNN to investigate the influence of weather on crops in smart farming where training is carried out using gated recurrent units. Regazzo *et al.* [25] have used convolution neural network towards solving classification problems using images of leafs. Another interesting work has been demonstrated by Cama-Pinto *et al.* [26] towards studying propagation of radio waves.

The research problems extracted from existing studies are manifold that demands to be addressed. Following are some critical area of problems viz. i) none of the existing studies using machine learning models have yet addressed the problems associated with data transmission considering resource constraints among sensors deployed on field, ii) studies are evaluated with accuracy ignoring possible latency and resources that are equally affected while performing on-field operations in PA, iii) existing studies have considered data gathered from one field or specific to one type of crop to perform prediction ignoring the role of actuators in PA, and iv) decision made by machine learning models offered only one predictive outcome without considering the challenged involved in relaying the information back to the field (to actuators).

The aim of the proposed scheme is to address the above-mentioned problem by presenting a decentralized architecture using machine learning. The value-added contribution of the study are as follows: i) the multi-tier decentralized architecture is presented to share the overall operation related to generalized applications of PA, ii) edge computing servers have been considered to address the speedily dissipated resources for sensor nodes, iii) a cloud environment has been considered where machine learning based analytical processing is carried out to control operations of actuators as well as data analysis for field information captured by sensors. The next section elaborates the adopted methodology of the study.

2. METHOD

The primary aim of the proposed study is to develop a decentralized computing environment that is capable of addressing the problem associated with overload data management in PA and hence the model is named as decentralized computing environment for precision agriculture (DCEPA). The implementation of the proposed study is carried out considering analytical research methodology where the intention is towards developing a flexible and streamlined transmission of agricultural field information considering cloud-IoT architecture with edge computing. The secondary aim of the study is towards outsourcing the task of data analytics to edge nodes in order to conserve the resources demanded by sensory devices on the field. The architecture for DCEPA is shown in Figure 1.

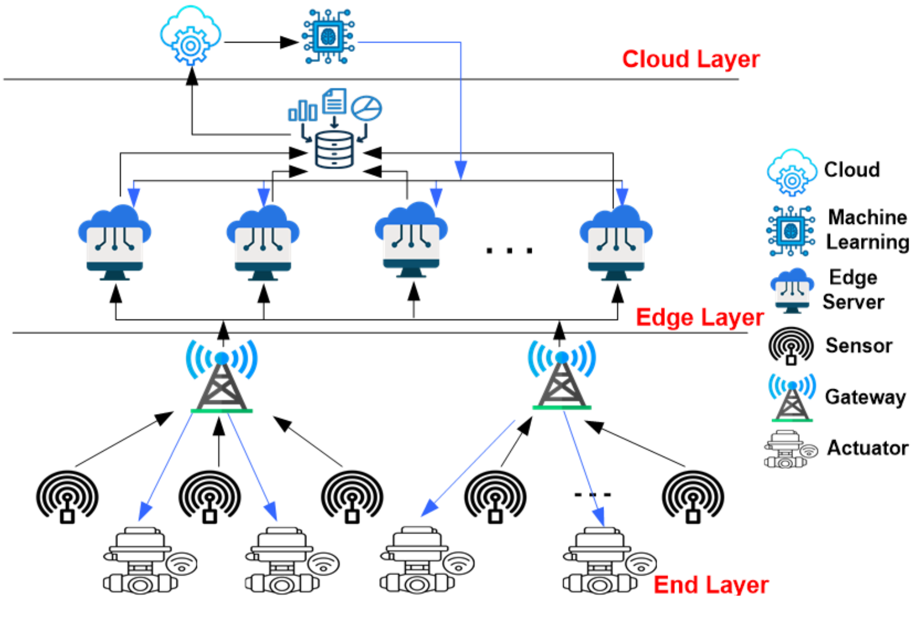

Figure 1. Architecture of DCEPA

According to Figure 1, it can be noted that proposed DCEPA is designed on 3-layered architecture that comprises of end layer, edge layer, and cloud layer. The agenda towards the adopted research methodology is mainly towards ensuring seamless and highly structured acquisition of field data from multiple origination point bearing heterogenous fields of agricultural data. Each layer interacts with each other to ensure that the final outcome assist in both enriched acquisition of field information followed by relaying of final decision-making commands to the actuators on the fields. The detailed information of each layer operations are as follows:

2.1. End layer operation

The end layer is the bottom layer in DECPA architecture which mainly comprises of two types of devices viz. i) sensory devices to capture field information and ii) actuators to carry out specific agriculture related task. Figure 2, shows mechanism and entities within end layer operation. As the proposed architecture is meant for generalization, hence, no specific use-case scenario is applicable; however, DECPA considers that these sensory devices could be soil sensor, climate and weather sensor, crop health sensor, air quality sensor, sensors for irrigation and water management, robotic and automation sensors. Each sensors collect the information from agricultural field using time division multiple access (TDMA) and forwards all the data to a local gateway node. The local gateway node carry out data fusion operation where the fused data is further forwarded to edge nodes in its upper layer. DECPA also considers inclusion of actuators which is mainly meant for executing certain agriculture related task after receiving the commands from local gateway node. The actuator considered in design of DECPA could be related to certain unmanned tractors or automatic water/pesticide sprinklers, or it would be some device that could capture selective information based on event criticality. All the sensors are interconnected to each other and performed their process of data acquisition and processing based on formation of network with other sensors. All the sensors are considered to be deployed with a definitive resources which information's are retained within the local gateway. As proposed DECPA targets a large-scale decentralized operation, it considers presence of various local gateway assigned to different farming areas in different geographical regions. All the local gateway further communicates with edge layer in order to carry out their respective task i.e., data fusion from information captured from sensory devices and relaying commands to actuators to carry out specific task.

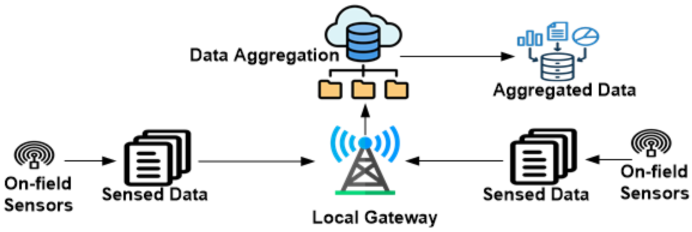

Figure 2. Mechanism within end layer

2.2. Edge layer operation

The proposed system of DECPA introduces edge layer in order to offer computing support towards proper resource management as shown in Figure 3. The rationale behind introducing edge layer are manifold. Conventional sensor-based approaches in PA usually rely on data-driven methodologies when each sensor is burdened with acquisition of voluminous information from agricultural farm followed by processing them. This phenomenon saturates excessive resources of sensors. Further, existing mechanism of sensor network indulge themselves into routing operations using sophisticated transmission protocol, which dissipates energy apart from the energy drained by its self-hardware-related operation by consistent monitoring. Further, the load of information processing differs from one sensor to another while implication of similar routing scheme may result in higher fluctuation and inconsistencies of performance of sensor. This could eventually lead to faster resource drainage along with sub-optimal quality of data acquisition process. Hence, DECPA introduces fog nodes which can address this challenges. The task of sensor node is just to acquire data and forward them to edge nodes where data fusion is carried out unlike existing approaches where aggregation and fusion is carried out within sensor nodes. This layer consists of multiple number of edge nodes which are connected in decentralized manner with each other syncing information gathered from all the local gateways from end layer. The edge nodes performs multiple task as follows: i) it fuses the data followed by preprocessing the data and forward the preprocessed data to next upper layer of cloud, ii) it identifies the load on each sensor along with monitoring their respective resources to carry out the task. In case, if edge node finds one of its sensors to have reduced resources, it identifies a neighboring sensor with sufficient resources and outsource/split the task of aggregating the sensory data. Accordingly, it alters the topology to ensure resources of each sensors are optimally used. iii) Finally, the edge node forwards hierarchies of commands to local gateway node which are then relayed to actuators.

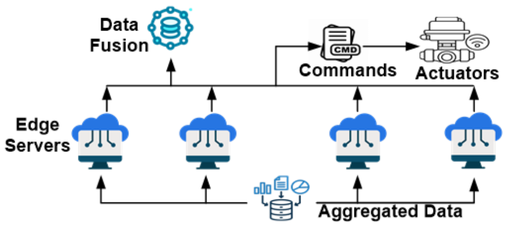

Figure 3. Mechanism within edge layer

2.3. Cloud layer operation

This is the top most layer of DECPA which is basically responsible to undertake some critical decision to ensure efficient operation of given smart field as shown in Figure 4. The primary task of this layer is to acquire the preprocessed information from edge layer. The preprocessed information from its bottom layer (edge layer) consists of on-field data along with status of sensor nodes. The preprocessed data is then subjected to various machine learning models which undertakes its final decision that is relayed back to edge nodes. The machine learning model used by DECPA performs following task: the model takes multiple input of preprocessed data, extracts features, and carry out its predictive operation. The objective function of this operation is to find out optimal sensor node with sufficient resources as well as make a sequential listing of nodes based on order of their resources. This information outcome significantly assists the edge node to instantly select a node with higher resources in cases some of the neighboring nodes are depleting its resources fastly. Another objective function of this layer is related to activating the actuator by relaying a specific command. The machine learning model perform its predictive analysis to forecast the instance of time, location, and selective operation to be executed by an actuator. As the complete operation is hosted under cloud environment managed by service provider, hence no specific concern of resource utilization in this layer is considered owing to assumption of high-end resources.

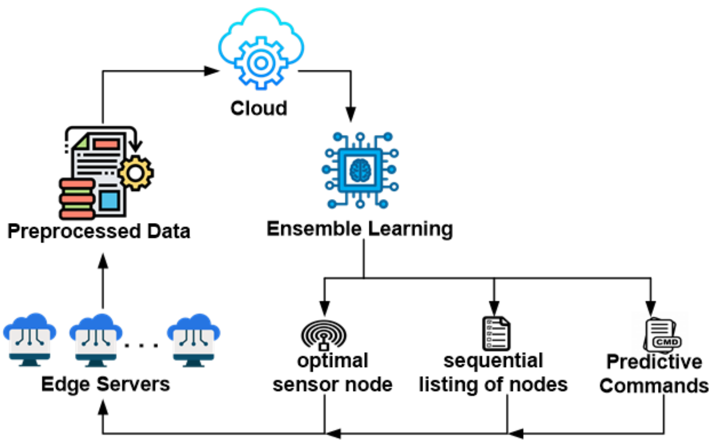

Figure 4. Mechanism within cloud layer

3. RESULTS

Prior to implement DECPA, it is noted that existing dataset for PA is usually image-based while string-oriented dataset is demanded in proposed study (owing to adoption of sensors). Hence, a synthetic dataset has been designed with 50,000 fields capturing information of field hypothetically designed. The study further considers 500 sensors, 10 local gateway nodes, and 4 fog nodes in simulation area of 1,100x1,500 m^2 with 7 discrete geographical farming location. Proposed DECPA has been testified with multiple machine learning models (e.g., LSTM, DNN, AE, and SVM) which are reported to be frequently adopted in existing literatures in PA. The performance metric considered are energy consumption, response time, accuracy, and latency. Table 1 showcases the numerical outcome of the varied combination of DECPA which states that DECPA performs optimally when combined with DNN. The accomplished outcome shows that DECPA-DNN to offer approximately 20% of reduced energy consumption, 18% of faster response time, 5% of increased accuracy, and 51% of minimized latency. For better understanding, the graphical representation of respective numerical scores are shown in Figure 5.

Table 1. Numerical accomplishment of DECPA

Approaches	Energy consumption (%)	Response time (s)	Accuracy (%)	Latency (s)
DECPA-LSTM	53.7	1.902	93.6	0.817
DECPA-DNN	27.8	0.578	98.7	0.181
DECPA-AE	38.2	2.671	95.6	0.622
DECPA-SVM	46.9	1.998	92.6	0.809

According to comparative analysis of Figure 5(a), it can be noted that LSTM and GNB induces more energy consumption which is mainly due to complexities associated with both the models when exposed to larger dataset. Similarly, response time for AE and GNB is noted to be quite higher that can be justified by constraints of this models towards working on sequential data along with training complexities Figure 5(b). The accuracy towards decision making by LSTM, SVM, and GNB are quite similar where scalability issues surfaces when interaction is performed by edge layer and cloud layer with seamlessly growing data Figure 5(c). The similar reason are also noted towards higher latency Figure 5(d). DECPA when combined with DNN offers an extensive ability to model complex relationship between all the input variables offering balance between accuracy and other performance metric. Apart from this, DNN is noted to quite capable of managing larger stream of dataset inclusive of multiple features. Hence, proposed system excels better result when combined with DNN in multiple perspective in PA overall exhibiting a cost-effective deployment.

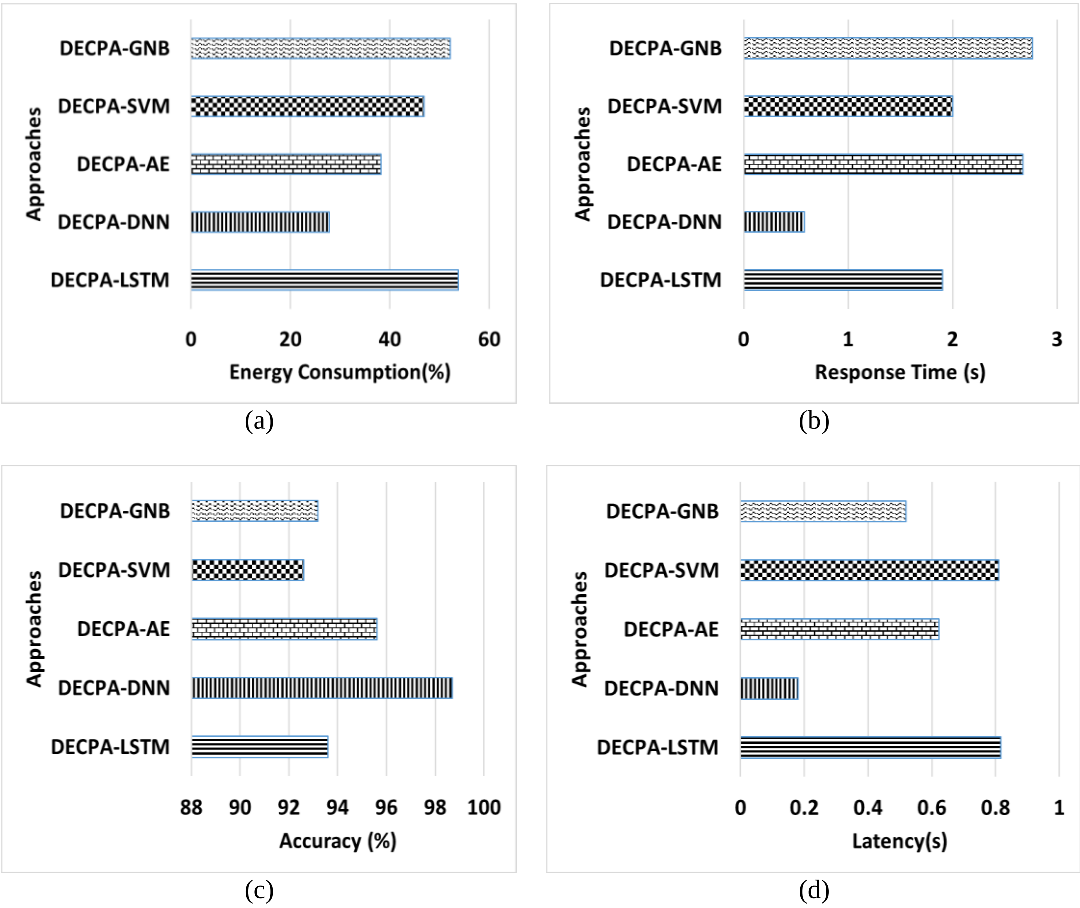

Figure 5. Evaluation outcome for (a) energy consumption, (b) response time, (c) accuracy, and (d) latency

According to the study's findings, the DECPA is successful, especially when combined with DNN. Significant performance gains were achieved by combining DECPA and DNN, including a 20% decrease in energy usage, an 18% speedup in response time, a 5% improvement in accuracy, and a 51% decrease in latency. These results demonstrate how well the system can manage resources and carry out tasks in extensive agricultural settings. One of the main arguments in favor of DNN's superiority over other machine learning models, such as LSTM, SVM, and AE, is its capacity to manage intricate datasets and variable relationships, which makes it more flexible in the face of changing field conditions and diverse sensor data.

It is evident from comparing these findings to earlier PA research that traditional approaches, which frequently rely on centralized systems or sensor-based aggregation, have trouble with resource efficiency and scalability. Prior studies have demonstrated the drawbacks of centralized data processing, which frequently leads to data congestion and excessive energy usage (e.g., LSTM and SVM in this study). The implementation of a multi-tier decentralized architecture with edge computing in this work, however, is a notable advancement. This strategy's primary advantage is its distributed resource management, which lessens the bottlenecks that traditional systems encounter. However, one drawback is that the system requires a significant number of sensors and computational power to operate completely, which could be difficult in settings with fewer resources. The sequential nature of the AE model's data processing, which has trouble handling big datasets and the demands of real-time decision-making in PA, is probably the reason why it unexpectedly fared poorly in terms of response time and latency.

The purpose of this study was to present a new decentralized computational framework for enhancing precision agriculture decision-making and resource efficiency. The findings highlight the value of integrating cutting-edge machine learning methods with edge computing to tackle issues in contemporary agriculture, such handling massive data sets and guaranteeing real-time responsiveness. The study offers insightful information about the advantages of a multi-layered, decentralized strategy. The system's scalability in even bigger, more varied agricultural contexts is still up for debate, though. Future studies might concentrate on examining other machine learning models for particular agricultural activities or refining the infrastructure for smaller-scale deployments. Furthermore, investigating how cloud-edge synergy and IoT integration might improve the framework would offer chances to increase the system's effectiveness and affordability.

4. CONCLUSION

The application of modern computing technology in agriculture, notably PA, has the potential to transform how we manage resources, increase crop yields, and make more informed, data-driven decisions. As global agricultural demand grows, tackling the difficulties of data overload and real-time processing is critical to ensure sustainable and efficient methods. This paper introduces the DECPA, a revolutionary method to resource management and decision-making that makes use of decentralized computing and powerful machine learning models. DECPA, particularly when paired with DNN, has shown higher performance in energy usage, response time, accuracy, and latency, making it a promising alternative for current agricultural operations. While some may claim that centralized systems or simpler models are sufficient, DECPA's scalability and efficiency, particularly in handling massive datasets and assuring real-time replies, make it the obvious choice for addressing PA's difficulties. Unlike previous systems, DECPA spreads computational load, resulting in better resource use and speedier decision-making. Future research should focus on improving DECPA for smaller-scale applications and investigating its interaction with IoT and cloud-edge technologies. The potential for increased adoption and impact is enormous, and improving these technologies will pave the path for more sustainable, efficient, and intelligent agricultural methods.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Kiran Muniswamy Panduranga	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Roopashree Hejjaji Ranganathasharma		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author.

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BIOGRAPHIES OF AUTHORS

Kiran Muniswamy Panduranga has completed B.E. (Information Science and Engineering) in the year 2005 from Sri Siddhartha Institute of Technology Tumkur, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India and M.Tech. (Computer Science and Engineering) in the year 2007 from AMC Engineering College Bangalore, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India. He has around 14 years of teaching experience. He is presently working as Assistant Professor in the Department of Computer Science and Engineering at Government Engineering College Hassan – 573 201, Karnataka, India. He can be contacted at email: mtech.kiran@gmail.com.

Roopashree Hejjaji Ranganathasharma has completed B.E. (Electronics and Communication Engineering) and M.Tech. (Computer Science and Engineering) from VTU, Belagavi, Karnataka, India and Ph.D. from CHRIST (Deemed to be University) Bengaluru, Karnataka, India. She has around 13 years of industrial experience and 6 years of teaching experience. She is currently working as Professor and Head in the Department of Artificial Intelligence and Data Science at GSSS Institute of Engineering and Technology for Women, Mysuru - 570 016, Karnataka, India and supervising 6 Ph.D. research scholars in Visvesvaraya Technological University. She can be contacted at email: roopashreehr@gsss.edu.in.