Edge-Cloud Remote Sensing Data-Based Plant Disease Detection Using Deep Neural Networks With Transfer Learning

Mazin Abed Mohammed, Abdullah Lakhan, Karrar Hameed Abdulkareem, Nouf Abdullah Almujally, Bourair Bourair Sadiq Mohammed Taqi Al-Attar, Sajida Memon, Haydar Abdulameer Marhoon, and Radek Martinek, *Senior Member, IEEE*

***Abstract*—These days, the disease among different plants has been increasing day by day. It is a very hard task for government institutions and farmers to collect data on plant diseases from different distributed lands among regions. Therefore, data collection, disease detection, and processing are the key issues for plants when they are suffering from healthy and unhealthy issues in different lands. This article presents edge-cloud remote sensing data-based plant disease detection by exploiting deep neural networks with transfer learning. The objective is to solve the aforementioned issues, such as data collection at a wide range, disease detection, and processing them with higher accuracy and time on different machines. We suggest transfer learning commutative fuzzy deep convolutional neural network (FCDCNN) schemes based on combinatorial optimization problems. The convex function optimizes the processing time and learning rate of data training on different edge and cloud nodes to collect more and more data from different plants from distributed lands. In the concave function, we predict the diseases among different plants, such as sugarcane, blueberry, cotton, and cherry with images, videos, and numeric values. The plant disease detection app uses edge nodes and remote satellite point cloud nodes to gather and train data using transfer learning and make predictions using fuzzy DCNN schemes that are more accurate and take less time to process. Simulation results show that FCDCNN obtained higher accuracy by 98% with less processing time 25% and trained with a higher ratio of data than existing schemes.**

***Index Terms*—Edge point cloud, fuzzy deep neural networks, plant disease detection, remote sensing data, transfer learning.**

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Mazin Abed Mohammed is with the Department of Artificial Intelligence, College of Computer Science and Information Technology, University of Anbar, Anbar 31001, Iraq, also with the Department of Telecommunications, VSB-Technical University of Ostrava, 70800 Ostrava, Czech Republic, and also with the Department of Cybernetics and Biomedical Engineering, VSB-Technical University of Ostrava, 70800 Ostrava, Czech Republic (e-mail: mazinalshujeary@uoanbar.edu.iq).

Abdullah Lakhan is with the Department of Computer Science, Dawood University of Engineering and Technology, Sindh 74800, Pakistan, also with the Department of Telecommunications, VSB-Technical University of Ostrava, 70800 Ostrava, Czech Republic, and also with the Department of Cybernetics and Biomedical Engineering, VSB-Technical University of Ostrava, 70800 Ostrava, Czech Republic (e-mail: abdullah.lakhan@duet.edu.pk).

Karrar Hameed Abdulkareem is with the College of Agriculture, Al-Muthanna University, Samawah 66001, Iraq, and also with the College of Engineering, University of Warith Al-Anbiyaa, Karbala 56001, Iraq (e-mail: khak9784@mu.edu.iq).

Nouf Abdullah Almujally is with the Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, Riyadh 11671, Saudi Arabia (e-mail: naalmujally@pnu.edu.sa).

Bourair Bourair Sadiq Mohammed Taqi Al-Attar is with the College of Medicine, University of Al-Ameed, Karbala 1238, Iraq (e-mail: bourair.alattar@alameed.edu.iq).

Sajida Memon is with the Department of Computer System Engineering, Dawood University of Engineering and Technology, Sindh 74800, Pakistan (e-mail: sajidamemons43@gmail.com).

Haydar Abdulameer Marhoon is with the Information and Communication Technology Research Group, Scientific Research Center, Al-Ayen University, 64001 Thi-Qar, Iraq, and also with the College of Computer Sciences and Information Technology, University of Kerbala, Karbala 1238, Iraq (e-mail: haydar@alayen.edu.iq).

Radek Martinek is with the Department of Cybernetics and Biomedical Engineering, VSB-Technical University of Ostrava, 70800 Ostrava, Czech Republic (e-mail: radek.martinek@vsb.cz).

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I. Introduction

These days, remote satellite data are crucial in green environments and in detecting many diseases in different plants and places. Many sources provide the collected data, such as NASA, ESA, and Digital Globe [1], [2]. These mentioned satellites collect multispectral data with diverse wavelengths, including different features, such as infrared, near, and thermal bands. These satellites can collect data on permitted areas in different regions, and images consist of many noises, null, and other values, too. Therefore, calibration, environment, and geographical geometrical correction on data (e.g., images and video) are required for preprocessing to decide on persistently collected data [3]. These data also require labeling and differentiating healthy and unhealthy plants on different processing nodes. For data consistency, the point cloud has been gaining much popularity and collects images and videos in 3-D with computer-aided design features [4], [5]. The point cloud is also considered an environment where these data and processes are executed with the given threshold values.

The edge point cloud is a new emerging processing computing environment that collects and processes plants' satellite remote sensing data, makes decisions on integrated machine learning approaches, and shares with institutions for further improvement [6]. The data modeling training and evaluation are on edge and cloud points to reduce the distance and noise issues between Earth plants on data. NASA and Digital Globe support many applications, such as water level, disease monitoring, and crowd-sensing, among different countries and their regions [7]. These studies [8], [9], [10] suggested deep convolutional neural network (DCNN) approaches for disease detection in different plants based on collected remote sensing data in terms of videos and images. These studies [11], [12], [13], [14], [15] considered unmanned drone vehicles with edge nodes to collect the remote sensing data of crops and detect their diseases based on DCNN.

However, there are many research issues with the current plant detection systems. 1) The existing systems only collect homogeneous limited sensing data with images. Videos and other numeric data could be beneficial, but they have higher processing time and less accuracy. 2) The existing systems used point clouds to train and collect satellite data. However, they have processing issues when the data contains more noise and extra vengeance issues.

This article introduces a novel transfer fuzzy deep neural network plant disease detection system based on edge point cloud Earth observations remotely sensed data. Based on the suggested system where implemented the transfer learning commutative fuzzy deep convolutional neural network (FCDCNN) schemes based on combinatorial optimization problems. The convex function optimizes the processing time and learning rate of data training on different edge and cloud nodes to collect more and more data from different plants from distributed lands. We consider the multimodel data such as video, images, and numeric data collected from remote sources, such as digital globe cloud and drone edge nodes. We consider heterogeneous resources, such as edge nodes and point clouds for data training and processing. The article makes the following contributions to the considered problem.

1) We present a novel transfer learning-assisted fuzzy DCNN approach, e.g., FCDCNN algorithm to process the multimodal plant data on different nodes. The FCDCNN algorithm consists of many schemes to process the data from collection to execution in the system.
2) We combine the training on cloud and edge because satellite cloud can collect huge amounts of land data compared to edge cloud. However, point clouds have less data accuracy due to higher delay in data collection and data consisting of different noises. Therefore, we present the edge and point-enabled transfer learning share scheme with the lightweight approach in the system. The suggested edge and point edge transfer learning schemes clean the nose and vengeance of data issues with less processing time and improve application training efficiency.
3) We devise a transfer learning approach to train and share the data training and evaluation on different nodes. For instance, point cloud-trained data are shared with the edge nodes for application processing with more accuracy and time.
4) We present the mathematical model with implementation with both concave and convex optimization for the considered problem.

The rest of this article is organized as follows. Section II is about the state of the arts. Section III is about formulation, and Section IV is about methodology. Section V is the performance evaluation. Finally, Section VI concludes this article.

II. Related Work

This part discusses existing methods and systems based on remote sensing data for plant disease detection. This study [1] presented the NASA-based crop detection system based on global digital remote sensing data. The Google Cloud services also implemented and collected remote sensing data from different satellites and nodes about different winter weather and plant diseases. However, this study only focused on the collected data from satellite networks.

The Nepal industry [2] investigated remote sensing data-based plant disease detection in dedicated regions for farmers. This study used invasive understories species sensors for crops and analyzed their plant disease status based on collected data. These studies exploited deep neural network approaches to get the features of plant disease data.

The plant nutrition against plant disease based on remote sensing data from satellite is investigated in this study [3]. The sensing data were collected and inserted into a deep neural network for feature extraction and prediction of nutrition deficiencies in plants.

This article [4] used the point cloud to collect remote sensing data for different crops based on 3-D images at different time intervals. The convolutional neural network is implemented to get the features from collected 3-D images and predict the plant disease with the diversity of collected data. However, this study only focused on specified areas to collect their data.

A multiplanet point cloud methods are suggested in these studies [5], [6] for species multisegmentation sensing data for plant disease. These studies consider the heterogeneous point clouds where data training and evaluation are done in parallel form to predict disease on data.

These studies [7], [8], [9], [10], [11], [12] exploited the autoencoder DCNN approach to predict nutrition deficiency, plant diseases, and correlated hyperparameters based on decision methods. The convolutional neural network trained, evaluated, and tested the imaginary models of the collected sensing data for decision. The plant cognitive spray requirement for unhealthy plants is also implemented in these systems. However, based on imaginary data, these data are trained and evaluated on the cloud nodes.

These studies [13], [14], [15] unmanned aerial vehicle (UAV) assisted edge cloud nodes for real-time remote sensing collection for plant data. These studies suggested fuzzy logic and multidecision methods based on deep neural networks for plant disease prediction based on crop sensing data based on UAV drone technologies. These studies [16], [17], [18], [19], [20] suggested probabilistic fuzzy methods integrated with the transfer learning based on hyperspectral imaging data of the crops collected based on remote satellites and drone technologies. These studies [6], [21], [22], [23], [24], [25], [26], [27], [28] suggested data fusion based on plant and fruit disease detection systems based on fuzzy methods in distributed 3-D sensing cloud data. These studies implemented and integrated the different baseline approaches, such as remote cloud sensing fuzzy deep convolutional neural

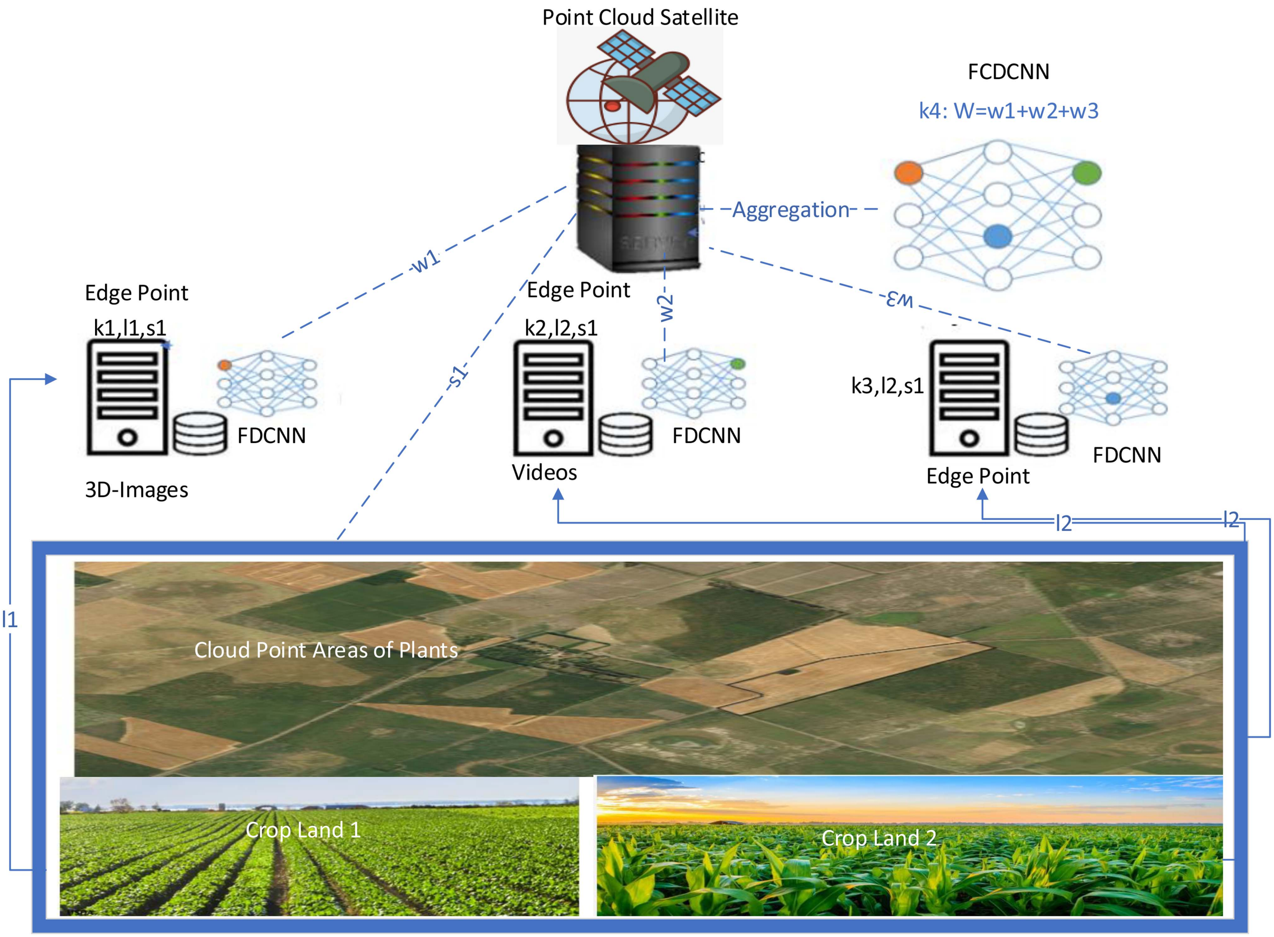


Fig. 1. Transfer learning deep neural network assisted plant disease detection system based on edge cloud point networks.

network (RSFDCNN) and edge sensing fuzzy deep convolutional neural network (ESFDCNN) methods, to classify and analyze the plant data for disease prediction in distributed land in terms of acres.

However, numerous research challenges persist in contemporary plant detection systems. All the existing systems solely gather uniform sensing data via images; nevertheless, videos and additional numerical data could prove advantageous, consuming fewer resources while achieving greater accuracy. The aforementioned studies only collected data based on unmanned drone applications on edge nodes that handle and train plant disease data. Nonetheless, resource scarcity issues arise when vast areas of plants exhibit numerous diseases and greater diversity. Therefore, we suggest the novel transfer learning integrated fuzzy deep neural network based on edge point cloud and consider multimodal data for plant disease detection in real-time.

III. Proposed Plant Disease Detection System

This study presents a novel edge cloud point-enabled plant detection system, transfer learning integrated at different nodes, and trained sensing data based on deep neural networks, as shown in Fig. 1. The proposed system consisted of elements, such as a point satellite cloud, distributed point edge nodes, and designated areas of crops for disease prediction and data collection, as shown in Fig. 1.

The satellite point cloud is a computing node that collects remote sensing data on crops from the satellite in the designated area at time intervals. For instance, the satellite point cloud takes pictures of plants morning, afternoon, and evening. The satellite collects remote sensing data in different formats, such as images, binary, and videos. We have created the socket programming-based application interface, where edge nodes have the same application interface for data analysis and results display of collected crop data.

The edge nodes are subnodes of cloud points that collect high-resolution data near the plant and train and evaluate it using a DCNN. We exploited transfer learning, where the training of plant data is performed at the local nodes, and offloaded the updated weights to the centralized point cloud for processing and decision-making.

The plants' locations and areas are already registered in the remote cloud point application programming interface and stored in the cloud for data collection and processing. The edge nodes and satellites collect the remote sensing data of different plants based on their types in different locations.

TABLE I
SYMBOL NOTATIONS

P	Application
T	Tasks of application P
R	Remote sensing data
r	Particular sensing data
D	Edge sensing data
K	Number of edges node
ϵ_k	Computing capability node k
ζ_k	Computing power of node k
L	Total number of crops lands
l	Particular crop area
C	Number of node
c	Particular cloud has V vms
ϵ_c	Computing capability node c
ζ_c	Computing power of node c
TTC	Transfer learning training on cloud points
TTE	Transfer learning training on edge cloud
S	Set of fuzzy
s	particular fuzzy set
X	Fuzzy non linear decisions
x	Particular decision
U	Number of updated weights of training
u	Particular updated weights
DCNN	Deep convolutional mechanism of training
V	Total number of virtual machines of C
Z	Number of combinatorial constraints
N	True and false attempts
J	Time zones
j	Particular time zone
Satellite	determined the satellite time and data
Edge	Determine edge time
TTC	Determines training time of data

A. Problem Formulation and System Model

The study considers the generic plant application P that consisted of different number tasks, e.g., $T = \{t = 1, \ldots, T\}$. Each task has a different tuple of attributes, e.g., plat data collection, training, analyzing, and prediction on different nodes. We consider the different sensing point computing nodes such as heterogeneous edge clusters and point clouds that collected the information from different locations. The distributed and ubiquitous edge nodes are represented by $K = \{k = 1, \ldots, K\}$. Each edge node k has storage and migration capability ϵ_k and central processing unit (CPU) ζ_k. We consider the heterogeneous clusters enabled virtual machines assisted point cloud which is implemented and located at a global satellite for capturing images, video, and numeric values. For instance, $C = \{v = 1, \ldots, VC\}$. Whereas, C is the cloud computing V is the total of the virtual machine implemented in the point cloud, and v is a specific virtual machine with different features in the point cloud.

We formulate the problem in the following way:

$$\text{Satellite} = \sum_{r=1}^{R} \sum_{v=1}^{V\in C} \sum_{t=1}^{T\in A} \frac{r, t, v}{\zeta_c}, \quad \forall r = 1 \ldots, R. \tag{1}$$

Equation (1) is the collection of data processing time of remote sensing of different point clouds in distinct satellites

$$\text{Edge} = \sum_{d=1}^{D} \sum_{k=1}^{K} \sum_{t=1}^{T\in A} \frac{d, t, k}{\zeta_k}, \quad \forall d = 1 \ldots, D. \tag{2}$$

Equation (2) is the collection of remote sensing data processing time from different placed edge nodes

$$\text{TTC} = \sum_{r=1}^{R} \sum_{c=1}^{C} \frac{\text{dcnn}[r, c, u]}{\zeta_c}. \tag{3}$$

Equation (3) is the training mechanism at point clouds based on transfer learning DCNNs

$$\text{TTE} = \sum_{d=1}^{D} \sum_{k=1}^{K} \frac{\text{dcnn}[d, k, u]}{\zeta_c}. \tag{4}$$

Equation (4) is the training mechanism at edge nodes based on transfer learning DCNNs.

The main objective of fuzzy training is to train partially remote sensing data on different nodes and make a partial decision about training on individual nodes. We accept both partially optimal data training based on fuzzy rules. We apply fuzzy logic to determine partial true training at different edge and point clouds based on the following way:

$$\text{Fuzzy} = \sum_{s=1}^{S} S(x) \frac{1}{1 + \text{TTC}, \text{TTE}.e^{x}}, \quad \forall r, d, \ldots, R, D. \tag{5}$$

We considered the nonlinear sensing data and applied the fuzzy rules to training as determined in (5).

We considered different constraints Z, such as accuracy, precision, recall, f1-score, processing time, deadline, failure, and resource leakage during the execution of applications in the point cloud and edge nodes.

The objective function as a combinatorial function is determined in the following way:

$$Z = \text{Satellite} + \text{Edge} + \text{TTC} + \text{TTE} + \text{Fuzzy}, \forall t = 1, \ldots T \in A. \tag{6}$$

Equation (6) is the objective function of the study.

We formulate the fuzzy combinatorial model based on transfer learning in the following way:

$$\max Z, \quad \forall C, K, A. \tag{7}$$

Equation (7) determines the maximum functions for all tasks of application and nodes.

Subject to

$$\text{Accuracy} = \sum_{z=1}^{Z} \frac{\text{True.Fuzzy}.z}{N}, \quad \forall z = 1, \ldots, Z. \tag{8}$$

Equation (8) determines the accuracy of all constraints based on fuzzy decisions

$$\min Z', \quad \forall C, K, A. \tag{9}$$

Equation (9) determines the minimized functions for all tasks of application and nodes.

Subject to

$$\text{Resource} = \sum_{z=1}^{Z} \frac{\text{True.Fuzzy}.z}{N}, \quad \forall z = 1, \ldots, Z. \tag{10}$$

Equation (10) determines the resource capability constraints while executing all training and validation of sensing tasks.

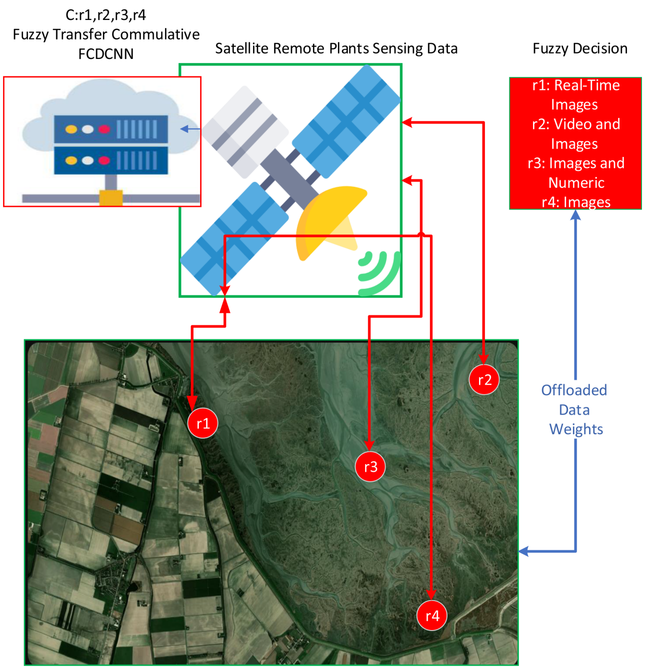


Fig. 2. Point cloud satellite plant remote sensing data processing.

IV. Proposed Fuzzy Transfer Learning Deep Convolutional Neural Network (FDCNN) Methodology

We present the FDCNN algorithm methodology, comprising different submethods, such as remote, edge training, scheduling resource allocation, and execution.

A. Point Cloud Plants Remote Sensing Data

The position of the point cloud is adaptive and ubiquitous in terms of satellite, where computing consists of speed and storage. We defined the point cloud movement to collect the sensing data from different locations, as shown in Fig. 2. We consider the point clouds C, where different computing cloud nodes are shown as c with their respective virtual machines. The point cloud collects different data modes, such as video recording, images, and numeric values from different plants and stores them in the cloud repository. We collected the R with a distinct data format and trained and evaluated it based on a FDCNN.

The main role of transfer learning is to train, test, and validate the data on different nodes, such as edge and cloud nodes. We trained the data weights on features, such as accuracy, f1-score, recall, and precision, with the fuzzy sigmoid function. We devise the fuzzy transfer learning commutative DCNN that trains all data based on their weights. We present the algorithm, as shown in the following in Algorithm 1.

In Algorithm 1, we defined these parameters, for instance, R, C, V, A, L, J. Whereas R is the remote sensing collection of data, C is the collection of cloud computing, V is the number of tasks of the application, A is the application, L is the total number of crop locations, J is the time zones when data is collected from different sensing nodes.

Algorithm 1: Satellite Point Cloud Remote Sensing Plant Data Scheme.

Input : R, C, V, A, L, J
1 **begin**
2 Collect Data From Plants L;
3 Time-Zone J;
4 **foreach** $(l = 1 \; as \; L)$ **do**
5 Capture 3D Images and LIDAR;
6 Determines: c, r, l, j: Time zones;
7 Input dataset;
8 **foreach** *(r=1 to R)* **do**
9 Convolutional layer;
10 Matrix$[c, r, l, j]$;
11 Feed-forward;
12 Split dataset train and test;
13 Iteration i;
14 Split.Matrix$[c, r, l, j]$;
15 Test.Matrix$[c, r, l, j]$;
16 Train.Matrix$[c, r, l, j]$;
17 Fully Connected all dataset evaluation;
18 Apply Fuzzy rules;
19 $e = \{0, 1\}$ Fuzzy probability based on equations (1, 3);
20 $w = \frac{1}{1+TTC,TTE.e^{x}}$[c,r,l,j];
21 Call Transfer Learning;
22 Share weights based on equation (3);
23 End Sharing;
24 End training;
25 End Main;

We collected and trained the datasets based on a fuzzy DCNN scheme that consisted of different processes, such as data collection in different time zones, training, validation, and testing, as shown in Fig. 3. We defined the inputs and training process in different layers, as shown in steps 1–10. Algorithm 1 takes the input as collected data, and collected data extracts their features, as shown in the metrics. We split the datasets into train, test, and evaluation and make predictions based on fuzzy based on partial true and false as determined in steps 11–25.

We collected data sensing data from cloud points from different plants in different time zones, as shown in Fig. 3. The data is trained on different constraints, such as the algorithm scenario has different steps, such as input convolutional neural network by 16 $\times$ 16 and fully connected layer along with fuzzy decision with updated weights, as shown in Fig. 3.

All the updated trains are shared with the edge nodes for further processing and execution. All the remote sensing data on the point clouds is shared with the edge nodes for the further closeness of plant disease detection with more accurate results. The remote covered the entire full region data; however, we exploited the edge nodes for particular areas and downloaded the trained weights from point clouds for executions. The transfer learning gained knowledge about point clouds and trained

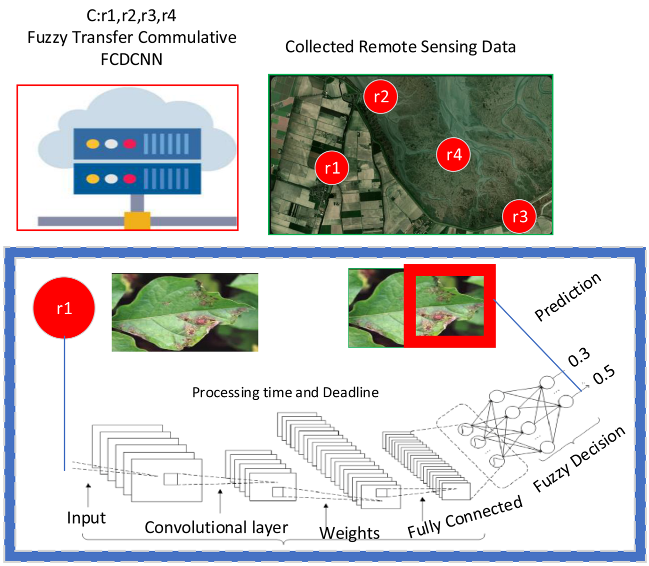


Fig. 3. Remote sensing training based on FCDCNN scheme.

and predicted particular diseases of plants on edge nodes with minimum delay and noise in the system.

B. Transfer Learning Between Edge and Point Clouds

We implemented transfer learning where different edge and cloud points shared their weights to predict disease from satellite and close ground based on edge and cloud point nodes. Transfer learning allows the exchange of weights for plant data prediction. We are considering two kinds of plant prediction: satellite plant and edge data.

We train, test, and validate the dataset fusion using a different number of layers. We have defined the different layers and depths of the proposed FDCNN. There are different layers, such as the input, output, and convolutional layers, with hidden layers 32 $\times$ 32. We train the datasets by 85% and 15% for validity and test on different nodes as defined in steps 11–25. Algorithm 2 takes the different parameters as input. For instance, R, k, T, L, J, whereas R collection of remote sensing data, k is the edge node, T total number of tasks, L is the location, and J is the time zone.

1) Algorithm 2 collects the images based on the drone and designated network very close to the land. The location is distinct and is less distant as compared to satellite sensing nodes.
2) We implemented the deep neural network with feedforward schemes to process the trained data based on updated weights, which are shared with the remote satellite sensing data.
3) We extracted all features of data with different edge points and converted them into a features matrix list.
4) The fully connected layer converts the features into a meaningful data format for data decisions.
5) The fuzzy rules are applied to the trained data for disease prediction and process the data on the given threshold as determined in steps 1–23.

Algorithm 2: Transfer Learning Assisted Edge Plant Data Collection and Processing Schemes.

Input : R, k, T, L, J
1 **begin**
2 Collect Data From Plants L;
3 Time-Zone J;
4 Analyze tasks;
5 **foreach** $(t = 1$ *to* $T)$ **do**
6 Initiated tasks and downloaded weight from point clouds;
7 **foreach** $(l = 1$ *as* $L)$ **do**
8 Video and Images Based on Drone Images;
9 Crop Plant Land: k, r, l, j, t: Time zones;
10 Input dataset;
11 **foreach** *(d=1 to D)* **do**
12 Slum scheduler for all tasks;
13 Matrix[$t \in A, d, l, j$]$\leq \epsilon_k$;
14 Transferred weights;
15 Split dataset train and test;
16 Iteration i;
17 features[t, k, d, l, j];
18 Test.features[t, k, d, l, j];
19 Train.features[t, k, d, l, j];
20 Fully Connected all dataset evaluation;
21 Apply Fuzzy rules;
22 $e = \{0, 1\}$ Fuzzy probability based on equations (2, 3);
23 $w = \frac{1}{1+TTC, TTE.e^{x}}$[k,t,d,l,j];
24 Call Transfer Learning;
25 Share weights based on equation (4);
26 End Sharing;
27 End training;
28 End Main;

6) All the edge nodes and point clouds are connected and transfer their trained weights with each other for more and more plant disease detection with higher accuracy and less processing time.
7) The epsilon is the fuzzy learning rate in an algorithm that allows the fuzzy decision based on partial true and false on the remote and edge sensing data.

The drone collects the data from different locations, e.g., L in different time zones with higher video recording and high-quality visual images.

V. Performance Evaluation and Experiments

In this part, we evaluated the performance of different systems and their implementation, databases, nodes, and resource characteristics. We designed the simulation on different parameters, such as language, runtime environment, experimental replica, resources, and operations, as shown in Table II. We have defined the different layers and depths of the proposed FDCNN. There are different layers, such as the input layer, output layer, and

TABLE II
POINT CLOUD AND EDGE PLANT SIMULATION PARAMETERS

Parameter	Description
Languages	JAVA, IoT Kotlin, Socket, Python
Run-time	Socket programming
Operating system	X86 virtualization
Simulation repetition	46 times
Environment	High performance computing
Drone edge layer	Server socket layer
Communication networking	Wireless technology
Input layer	500 layers
Output layer	700 layers
Convolutional layers	32×32

TABLE III
PLANT DISEASE DETECTION APPLICATION TASKS

Task	Description	Remote-data	Edge-data
t1	Plant surveillance	Image	Video Recording
t2	Location	Coordinates	Coordinates
t3	Plant results	Images	Images, video
T	Data	Size	Nodes
2000	Multimodal	2 GB	Edge cloud

TABLE IV
PLANT DATASETS

Plant	Data	Node	Area	Time
Cotton	3000 Images	Edge cloud	15000 acre	Morning
Cherry	5000 fusion	Edge cloud	20 000 acre	Morning
Sugar-cane	4000 fusion	Edge cloud	18000 acre	Morning
Blue-berry	1000 fusion	Edge cloud	19000 acre	Afternoon

convolutional layer with hidden layer 32 × 32, as we defined in Table II.

Table II shows the simulation parameters of the experimental implementation of crop disease detection application with different values and characteristics. Table III shows the plant disease application tasks' characteristics and data size with data types. We consider multimodal data, such as image, video, and numeric data, which is collected from different point clouds and edge nodes for plant disease detection, as shown in Table III.

A. System Implementation and Datasets

We collected the different data fusion datasets of plants from different sources, improved their labels, and processed them on remote and edge cloud nodes. This data fusion, such as sugarcane, cherry, and blueberry datasets, is divided into remote and edge cloud sensing classes and includes 2 GB of 3-D images of diseased plants, damaged crop leaves, and healthy plants. We created the plant detection disease system based on socket programming, where all runtime compilers are designed based on X86 cross-platform for execution. We designed the different interfaces for simulation, such as the controlled application interface, remote sensing interface, and edge cloud sensing interface, for disease detection in the system. We have trained, tested, and validated different samples of images, such as cotton, sugarcane, blueberry, and cherry, as shown in Table IV. We defined the

TABLE V
COMPUTING RESOURCES

Node	Resource	Storage	CPU	Placement
c1	Hybrid VMs	5000 GB	Core i7	Point cloud
c2	Hybrid VMs	10000 GB	Core i9	Point cloud
c3	Hybrid VMs	10 TB	Core i7	Point cloud
k1	Edge	100 GB	Core i5	Edge cloud
k2	Edge	1000 GB	Core i3	Edge cloud
k3	Edge	1 TB	Core i5	Edge cloud

TABLE VI
CONVEX OPTIMIZATION TIME COMPLEXITY RESULT ANALYSIS

Method	Plant	Data	Node	Z' (Minutes)
FCDCNN	Cotton	18000	Edge cloud	20
RSFDCNN	Cotton	19000	Edge cloud	50
ESFDCNN	Cotton	20000	Edge cloud	60
FCDCNN	Cherry	7000	Edge cloud	18
RSFDCNN	Cherry	7000	Edge cloud	45
ESFDCNN	Cherry	7000	Edge cloud	55
FCDCNN	Sugar-cane	5000	Edge cloud	16
RSFDCNN	Sugar-cane	5000	Edge cloud	48
ESFDCNN	Sugar-cane	5000	Edge cloud	57

different data samplings in the dataset for the article's result analysis.Table IV shows the remote and edge sensing data for the different crops with different characteristics. Fusion shows the data types executed during the system's training, testing, and validation.Table IV shows the remote and edge sensing data with the different crops, as shown with different characteristics.

B. Result and Discussion

In this part, we discuss the numeric result analysis and a graphical evaluation of the performance of different methods on different plant data based on statistical concave and convex binomial distributions.

We integrated the different baseline approaches, such as RSFDCNN and ESFDCNN methods we discussed in the related work. We compared the existing approaches with the proposed algorithmic schemes in the system. Table VI shows that all the plant data with the higher accuracy have less processing time with the FCDCNN as compared to existing baseline approaches. The main reason is that we have exploited transfer learning, where trained weights are shared to optimize both concave and convex optimization for the applications in the system. The existing baseline approaches did not consider the transfer learning training on remote and edge sensing data with less accuracy and higher processing with the partial true and false results, as shown in Table VI.

We evaluated the result analysis in tradeoff combinatorial problems, such as concave and convex optimizations, where time and accuracy have higher frequency on the method performance to determine disease in plants. All the existing studies only suggested methods to solve the concave optimization problems on the plant data; however, they have less accurate results with the higher frequency of processing time and resource failure on different computing nodes.

TABLE VII
GROUND TRUTH DATA FOR THE PLANT DISEASE BENCHMARKS STAGE WITH RESULT ANALYSIS

Method	Plant	Accuracy	Recall	Precision
FCDCNN	Cotton	98.5	0.98	0.98
RSFDCNN	Cotton	83.5	0.89	0.84
ESFDCNN	Cotton	80	0.85	0.83
FCDCNN	Cherry	92.2	0.91	0.98
RSFDCNN	Cherry	89.5	0.82	0.80
ESFDCNN	Cherry	81	0.83	0.81
FCDCNN	Cherry	98.2	0.98	0.98
RSFDCNN	Cherry	90.5	0.89	0.83
ESFDCNN	Cherry	89	0.88	0.84

We have compared the results of different baselines and proposed algorithms for different samplings of plant data. Ground truth data of plant disease with datasets benchmark stages, such as offloading, scheduling, and prediction, are evaluated with different constraints. For instance, time, resources, accuracy, recall, and precision, as shown in Table VII consisted of different metrics. Table VII shows that the proposed scheme optimized both concave and convex optimization statistical functions with prediction and processing on different plant data using different baseline approaches. We combined remote sensing data from point clouds and edge drone-collected data on distributed land regarding acres.

C. Cases of Implemented Datasets

In the experiment, we consider data fusion data in a dataset where different objectives are difficult to achieve when time, resources, and classification accuracy are constraints in the distributed computing nodes on remote sensing data. In this case, we are considering different nodes, where each node has different computing capabilities and resources. Therefore, maintaining time is very difficult. Another case is resource scalability, when huge amounts of data are offloaded for training, testing, and validation. Therefore, we need to offload data from the balance form. The final but not least difficulty is accuracy when data has many forms and features on the different nodes. Therefore, in the simulation, we divided and experimented with our problem combinatorially and optimized all constraints related to plant disease data in the system.

We evaluated the performance of different methods in concave optimization with different constraints and metrics such as accuracy, recall, and precision for all data. We obtained optimal results as compared to existing studies. The main reason is that existing studies only focus on accuracy and can only train the current data weights with the available resource capability. However, it has less accuracy when the data and complexity increase in the plant disease for dedication and loss to farmers' economics for productions. We executed the remote sensing data with different diversity in tasks such as 10 000 and identified which plant was healthy and suffered from any disease. We also analyzed the results based on fuzzy logic with the higher ratio of predication diseases among different plants, as shown in Fig. 4. The confusion matrix shows the overall result analysis

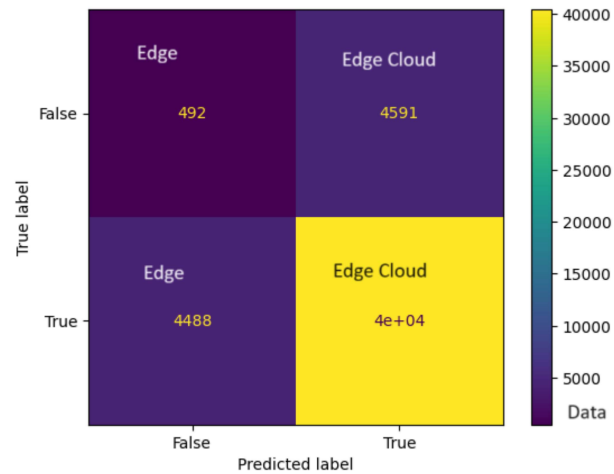


Fig. 4. Confusion matrix of training of remote sensing data on transfer learning different edge cloud nodes.

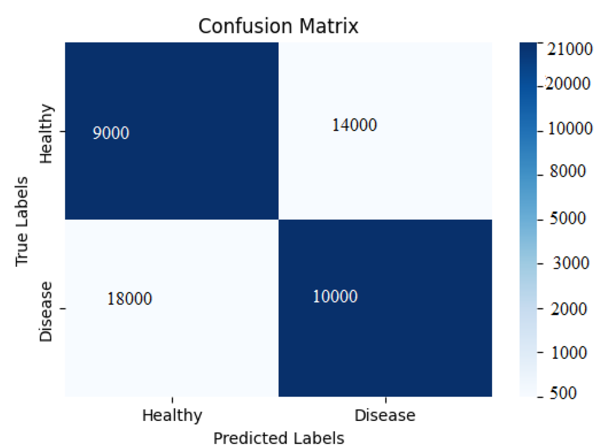


Fig. 5. Confusion matrix on trained plant data for healthy and disease detection.

report of training with the transfer learning based on DCNN about healthy and nonhealthy plants on the collected data. We consider the prediction and scheduling problem a combinatorial problem, whereas concave problems are considered classification and convex and scheduling problems. Fig. 4 shows the result analysis of the convex function where we determined the confusion matrix for the data training on different edge cloud nodes. Because we determine the plant disease prediction on the different nodes to maximize more and more concave accuracy function. However, to remove the confusion, we added the confusion for plant disease detection with higher accuracy, as shown in Fig. 5. Fig. 5 shows a confusion matrix where we labeled the disease and healthy plants with the different 21 000 images based on a convolutional neural network. The main motivation of the confusion matrix is to show the refinement of images, whether the plant is healthy or the disease identified from collected images in our method.

We are considering the multimodal data such as images, video, and numeric values; the disease prediction is diverse at different nodes and shares their weights on different to improve the prediction accuracy and minimize the training and processing

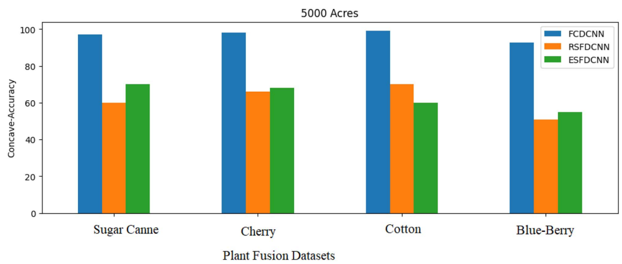


Fig. 6. Different plant data processing with concave accuracy.

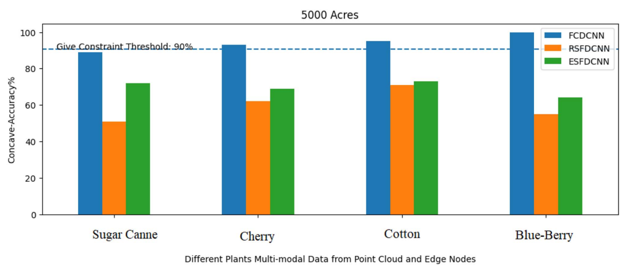


Fig. 7. Different plant data processing with concave accuracy under given threshold values.

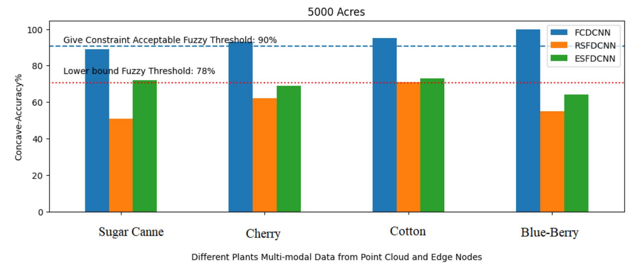
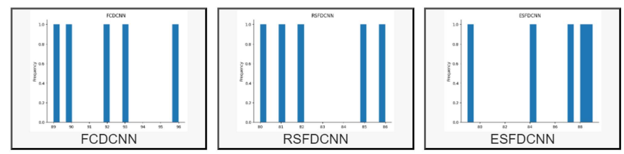


Fig. 8. Upper bound and lower bound accuracy of different plant disease.



t1	92	82	79	t1	92	82	79	t1	92	82	79
t2	90	85	88	t2	90	85	88	t2	90	85	88
t3	89	86	84	t3	89	86	84	t3	89	86	84
t4	93	81	87	t4	93	81	87	t4	93	81	87
T	96	80	89	T	96	80	89	T	96	80	89

Fig. 9. Tradeoff performances of methods for higher ratio of predication of plant disease.

time for application tasks. We analyzed the categorical collected and cumulative data rows that are 50 000 in the confusion matrix, as shown in Fig. 4. We determined that the edge node has less processing speed and less training data for complex work, with a poor result of about false 492. However, edge-cloud transfer learning weights have higher prediction with the fuzzy decision, which is about 4591 with false values. Therefore, true labels and predicated labels with true and false data prediction improve on edge cloud nodes when they are using transfer learning and sharing their weights for plant disease prediction in the system, as shown in Fig. 4. Therefore, our proposed scheme is more optimal in both combinatorial types of functions for plant disease data in distributed land acres.

We can improve the plant disease prediction with the higher ratio of concave function accuracy with the proposed scheme, as shown in Fig. 6. We considered the different plants' disease remote and edge sensing data, such as sugarcane, cherry, cotton, and blueberry as shown in Fig. 6, as shown in the x-axis and y-axis shows the accuracy of the methods to run these data and predict the plant disease with the more accuracy. Fig. 6 shows that the proposed idea and scheme have higher accuracy with a different data diversity than existing methods. The processing time consisted of offloading time between edge nodes to the point cloud, execution time, and training and sharing time on updated data weights. Therefore, considering that the availability of resources is adaptable and scalable, this is not true on the edge nodes. Therefore, we connect edge and cloud nodes to collect and process data more accurately and on time. Fig. 7 shows that the proposed scheme predicted and executed all plant's remote and edge sensing data with true partial and partial false based on the given threshold values in the experiment part. The threshold is that the prediction must have good accuracy and a higher ratio than 90%, which is more appropriate for the correct results on the given and trained plant data on the different edge and cloud nodes. Fig. 7 shows that FCDCNN is outperformed than RSFDCNN, and ESFDCNN for all given plant data for prediction and execution. Fig. 8 shows that the proposed scheme predicted and executed all plant's remote and edge sensing data with true partial and partial false based on the given upper bound and lower bound threshold values in the experiment part. The upper bound threshold is set at a level equal to 90%. The lower bound is also acceptable with fuzzy partial true and partial false values to detect plant diseases but with less accurate results during experiments. Fig. 8 shows that FCDCNN outperforms RSFDCNN and ESFDCNN in both upper and lower bound limits during experiments. Fig. 9 shows plant data's numerical and graphical categorical result analysis with different metrics such as accuracy, recall, and precision. Fig. 9 shows that all application tasks have higher accuracy, recall, and precision on different plant data when they are executed for prediction and analysis on different nodes based on suggested schemes. For the experiment, we only chose the fitted and best results from the experiments; we ignored the bad results due to resource and deadline failure during an experiment in the simulation.

However, still with the best result, Fig. 9 shows that FCDCNN outperformed RSFDCNN and ESFDCNN in both upper bound and lower bound limits during experiments.

VI. Conclusion and Future Work

The main finding of this was to introduce a methodology titled edge-cloud remote sensing data based plant disease detection using deep neural networks with transfer learning, aiming to address the aforementioned hurdles, such as broad-scale data collection, disease identification, and processing with heightened precision and efficiency across diverse platforms. We proposed using transfer learning in conjunction with FCDCNN schemes rooted in combinatorial optimization problems. The convex function was employed to optimize data training processing time and learning rate across various edge and cloud nodes to enhance data acquisition from various plants in distributed locations. Conversely, the concave function was utilized to prognosticate diseases prevalent among distinct plant species, such as sugarcane, blueberry, cotton, and cherry, leveraging images, videos, and numerical values. We combined a plant disease detection app that uses edge nodes and remote satellite point cloud nodes to make it easier to collect data and train the app through transfer learning. This lets us make predictions using fuzzy DCNN schemes that are more accurate and take less time to process. The simulations confirmed that FCDCNN was more accurate than other methods, as discussed in the result analysis.

However, the proposed work has many limitations. In the future, we will consider these constraints, such as economic impact, processing cost, and security, which have not been part of the proposed system. In future work, we will extend our plant disease detection system with these constraints and improve its efficiency with more optimal results regarding security, cost, and economical types for the government and farmers.

Data-Statement Availability

We have downloaded the sugarcane data for the experiments.[1] It comprised 10 000 data samples of healthcare leaves and unhealthy sugarcane leaves in different distributed land acres. We have exploited the mix of remote sensing data and edge cloud data related to cotton.[2] However, we will share mixed data soon on the public repository. We have mixed data, as we publically uploaded it on GitHub.[3]

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Mazin Abed Mohammed received the B.Sc. degree in computer science from the College of Computer, University of Anbar, Ramadi, Iraq, in 2008, the master's degree in IT from Universiti Tenaga Nasional, Kajang, Malaysia, in 2011, and the Ph.D. degree in biomedical computing and AI from Universiti Teknikal Malaysia Melaka, Melaka, Malaysia, in 2018.

He is currently an Associate Professor with the Department of Information Systems, College of Computer Science and Information Technology, University of Anbar. His research interests include artificial intelligence, medical image processing, machine learning, computer vision, computational intelligence, IoT, biomedical computing, bioinformatics, and fog computing.

Abdullah Lakhan received the B.E. degree in software engineering from the Mehran University of Engineering and Technology, Pakistan, in 2008 the M.E. degree in information technology from Mehran University of Engineering and Technology, Pakistan, in 2012 and the Ph.D. degree in computer science and technology from Southeast University China, in 2020.

He is currently an Assistant Professor with the Dawood University of Engineering and Technology, Karachi, Pakistan. He has more than ten years of experience teaching and researching at the university level. He has authored or coauthored more than 100 high-quality Level 1 and Level 2 conference papers and journal articles.

Prof. Lakhan is a Reviewer and a Guest Editor for Level 1 and Level 2 journals. He has co-organized several international conferences and regularly serves as a Peer Reviewer and Committee Member for international conferences and journals.

Karrar Hameed Abdulkareem received the B.S. degree in computer science (artificial intelligence) from the University of Technology, Baghdad, Iraq, in 2007, the M.S. degree in computer science (internetworking technology) from the Universiti Teknikal Malaysia Melaka, Durian Tunggal, Malaysia, in 2016, and the Ph.D. degree in computer science and information technology from the Universiti Tun Hussein Onn Malaysia, Parit Raja, Malaysia, in 2021.

His research interests include multicriteria decision making, data science, biomedical computing, and fog computing.

Nouf Abdullah Almujally received the Ph.D. degree in computer science from the University of Warwick, Coventry, U.K., in 2022.

He is currently an Assistant Professor in computer science with the Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia. His research interests include human–computer interaction, artificial intelligence, machine learning, deep learning, and computer-based applications.

Bourair Sadiq Mohammed Taqi Al-Attar received the Ph.D. degree in computer science from University Science Islamic Malaysia, Malaysia, in 2018.

He is a Personable Lecturer driven to inspire students to achieve personal and academic success. Offer lecturing and team leader experience with a wealth of knowledge in developing and implementing educational technology tools and applications in the classroom. Utilize creative teaching strategies to engage students fully in the learning process.

Sajida Memon received the B.S. and M.S. degrees in computer science from the Dawood University of Engineering and Technology, Karachi, Pakistan, in 2001 and 2023, respectively.

She is a Research Scholar with the Dawood University of Engineering and Technology. She has authored or coauthored many papers in intelligent transport, deep learning, machine learning, digital healthcare, and energy sustainability.

Haydar Abdulameer Marhoon received the Ph.D. degree in computer networks from the University of Uttara Malaysia, Malaysia, in 2017.

He is currently with the Information and Communication Technology Research Group, Scientific Research Center, Al-Ayen University, Thi-Qar, Iraq; and the College of Computer Sciences and Information Technology, University of Kerbala, Karbala, Iraq.

Radek Martinek (Senior Member, IEEE) was born in Czech Republic, in 1984. He received the master's degree in information and communication technology from the VSB—Technical University of Ostrava, Ostrava, Czechia, in 2009.

Since 2012, he has been a Research Fellow with the VSB—Technical University of Ostrava. In 2014, he successfully defended his dissertation thesis titled "The Use of Complex Adaptive Methods of Signal Processing for Refining the Diagnostic Quality of the Abdominal Fetal Electrocardiogram." In 2017, he was an Associate Professor in technical cybernetics after defending the habilitation thesis titled "Design and Optimization of Adaptive Systems for Applications of Technical Cybernetics and Biomedical Engineering Based on Virtual Instrumentation." Since 2017, he has been an Associate Professor with the VSB—Technical University of Ostrava. He has authored or coauthored more than 200 journals and conference papers in his research areas. His research interests include digital signal processing (linear and adaptive filtering, soft computing-artificial intelligence and adaptive fuzzy systems, nonadaptive methods, biological signal processing, and digital processing of speech signals), wireless communications (software-defined radio), and power quality improvement.