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Optimized routing algorithm with AlexNet-ShuffleNet for plant leaf disease and infectious classification in IoT

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ABSTRACT

In agriculture, utilizing images to detect plant leaf diseases is a vital area in precision farming. Typically, trained professionals physically inspect plant tissues to identify disease range. Nowadays, AI has made foremost paces in detecting and classifying plant diseases. Moreover, Internet of Things (IoT) has several applications, containing Agricultural-IoT (AIoT), which is considered to elevate agricultural yields. This paper intends to develop an approach in IoT for plant disease classification. Initially, simulation of IoT is done and the IoT nodes route sensed plant leaf images by proposed Serial Exponential Golf Optimization Algorithm (SEGOA), which is established by modifying Golf Optimization Algorithm (GOA) using Exponential Weighted Moving Average (EWMA) to the destination, where plant leaf disease detection is executed. To extract the RoI, CNN is used to discover diseased part in plant leaf. Then, plant leaves are classified as healthy and diseased subclasses by employing AlexNet-ShuffleNet. Moreover, the disease types are classified more into fungal/bacterial/viral infection using the AlexNet-ShuffleNet. Performance of adopted work is assessed by utilizing the metrics, such as energy, accuracy, sensitivity, and specificity. Overall outcome of AlexNet-ShuffleNet give a promising result, such as accuracy of 94.6%, sensitivity of 98.7% and specificity of 94%.

Keywords: *IoT, Routing, Disease detection, Plant disease, Deep learning, optimization.*

Artificial Intelligence	AI
Generative Adversarial Networks	GAN
Deep Learning	DL
Base Station	BS
Rectified Linear Unit	ReLU
Batch Normalization	BN
Convolutional Neural Networks	CNN
Exponential Weighted Moving Average	EWMA
Golf Optimization Algorithm	GOA
Internet of Things	IoT
Serial Exponential Golf Optimization Algorithm	SEGOA
Local Binary Patterns	LBP
Class Activation Mapping	CAM
Machine Learning	ML
Rectified linear unit	ReLu
Indian Council of Agricultural Research	ICAR

INTRODUCTION

The IoT has become increasingly prevalent in various technology fields, including advanced farming, advanced home systems, wearable devices, smart cities, smart villages, and more. By enabling communication and coordination between physical objects, the IoT allows for the sharing of information and decision-making.

Through the use of advanced technologies, like communication networks, sensor networks, and internet protocols, traditional objects can be transformed into intelligent and connected smart objects. Moreover, the early detection of disease outbreaks through IoT technology has the potential to promote sustainable advancement in agriculture, by facilitating sensible usage of insecticides. Predicting disease attacks early is crucial in effectively controlling the spread of a disease [5]. A-IoTs has emerged as a vital tool for quickly gathering videos of field and atmosphere data in recent years. In today's precision agriculture, the use of IoTs is expected to revolutionize the way we collect and detect images of plant disease. With the help of mobile devices and on-site video surveillance, images of plant leaf disease can be collected and uploaded, and a diagnosis can be automatically provided in a timely and accurate manner [10].
One significant feature of precision agriculture is the usage of image evaluation to identify plant diseases. Previously, professionals would visually look through seriousness of plants disorders. Henceforth, with the evolution of IT and usage of digital cameras in field of agriculture, skilled schemes for management and cultivation have attained popularity. This has greatly affect plant production. As plants play a vital position in human life, it is important to implement thorough mechanisms for classifying and studying plant diseases [4]. Mainly, the usage of expert systems to detect and characterize diseases often depends on the knowledge and skills of professionals, resultant in significant expenses and limited efficacy [1]. Several types of diseases, integrating leaf rust, bacterial blight, Downey mildew, powdery mildew, and brown spot, pose a threat to plants, making timely detection essential in reducing their impact [17]. Even though, constant supervision by specialists might be financially burdensome and time-consuming, evaluating it challenging for farmers to execute. It is important to have a method that is both effectual and essential for classifying diseases according to the symptoms displayed on plant leaves. Computer vision technology gives a convenient answer with its automated image-based process control, robot guidance capabilities, and inspection. Integrated to conventional mechanisms that rely on human eyes, deep learning approaches offer much faster and more accurate recognition and plant disorder classification. With the utilization of photographic images of these infections, professionals may effortlessly educate, educate, diagnose, and analyse plant diseases [19].
In order to meet growing request for timely and accurate recognition of plant leaf infections, it has become crucial to leverage the power of IoTs and automate the process. Nowadays, deep learning has arisen as a highly effective method for automating image classification and recognition. However, to achieve optimal results, a large count of annotated training samples is needed. To address this requirement, image modification techniques, such as scale, flip, translation, rotation, and random crop have become widely used for expanding datasets. Additionally, to enhance the diversity of training images, the use of GANs and their differences has been selected to generate new examples across several image data sets [7]. IoT technology has the potential to greatly enhance how to handle plant diseases. It can lead to increased crop production, less waste, and a more consistent food supply. Moreover, it can decrease the environmental consequences of agricultural activities. Sensors that employ IoT technology can identify plant diseases in their early stages, permitting for immediate action and reducing the likelihood of crop losses. These sensors can continuously keep an eye on the health of the plants, offering real-time information regarding the health of the plants, temperature, humidity, and several other environmental elements. Growers and scientists can keep an eye on the health of the plants from a distance and get warnings when diseases are identified, allowing for fast action to be taken. Sensors that use IoT technology can provide more precise diagnoses of plant diseases, lowering the risk of improper diagnosis and enhancing the outcomes of treatment.
The prime aim of the work is to examine a DL mechanism for proficiently categorizing plant diseases in an IoT framework. Here, the study simulated the IoT environment and employed an algorithm, SEGOA, which is an adaptation of the GOA with the EWMA, for routing the captured plant leaf images from the fields to the designated destination for disease recognition. To spot the infectious part in leaf, work utilized a CNN to extort the RoI. At last, for perfect classification into healthy and diseased subclasses, the plant leaves were trained employing the AlexNet-ShuffleNet structure. Moreover, the plant disease kinds are classified into fungal, bacterial, or viral infections using the AlexNet-ShuffleNet.

The main contributions of the presented method are specified below:

- To create an optimization algorithm, SEGOA, by improving GOA with the concept of EWMA, and employ it for the data transfer in IoT.
- To identify plant diseases and perform infectious classification using AlexNet-ShuffleNet.
- To assess how well the presented strategy works, employs measurements, like energy, specificity, accuracy, and sensitivity.

The work begins with an introduction at section 1. Next, it explains past research on detecting plant diseases in segment 2. Section 3 presents a model of an IoT. The fourth section shows presented approach. Section five discusses the results. Finally, the last part was the conclusion.

1. Literature Survey

Following segment points up prior studies and researches concerning identification of infectious plant leaves.
Hosny Khalid M *et al.,* [1], investigated the efficacy of a deep CNN model in capturing nuanced, high-level representations of plant leaf images. Anchored in traditional LBP factors, the research uncovered crucial insights on the detection of local

texture details within images. Striving for comprehensiveness, method was rigorously tested and examined on openly obtainable datasets, containing Apple Leaf, Grape Leaf, and, Tomato Leaf showcasing a remarkable performance in detecting plant diseases. Masood Momina *et al.,* [2] initiated MaizeNet, a DL mechanism for specific detection and categorization of leaf infections in maize crops. They utilized an advanced Faster-RCNN algorithm, integrated ResNet-50 architecture with spatial-channel attention, to extort distinct factors from images. These features were then grouped into diverse disease categories. MaizeNet was examined to utilize the Severity and Corn Disease dataset, which integrated images of three maize infections classes taken under varying and challenging conditions.

Shovon Md Sakib Hossain *et al.*, [3], introduced PlantDet, a compelling deep ensemble mechanism integrating InceptionResNetSV2, Xception, and EfficientNetV2L models. Through the incorporation of effectual data augmentation, preprocessing methods, and manifold layers, containing L2 regularizers and a PReLU activation function, as well as a Global Average Pooling layer and additional Dense layers, scholars effectively addressed issues of overfitting and underfitting while maintaining better performance. By testing their mechanism on the Betel Leaf dataset, they were able to demonstrate its superior performance compared to existing strategies, including other robust ensemble approaches. Furthermore, the authors utilized the techniques of Grad-CAM and Score-CAM to provide further insights into the strategy's efficacy and convoluted on how DL mechanisms operate on this multifaceted dataset. Sunil C. K *et al.,* [4], investigated identification of two common disorders in cardamom plants, namely Colletotrichum Blight and Phyllosticta Leaf Spot, as well as three grape disorders, namely Esca, Black Rot, and Isariopsis Leaf Spot. To effectively identify plant disorders, deep learning was the preferred technique, and the scholars specifically utilized U2-Net to get rid of pointless environs in input images by selecting multiscale factors. For the detection of cardamom plant infections, authors adopted EfficientNetV2 mechanism, and comprehensive arrays of assessments were executed to assess its performance compared to extra methods, like CNN and EfficientNet.

ZHIYAN LIU *et al.,* [5] presented an innovative solution for disease identification by computer vision. However, this method can only identify diseases after they have already appeared. As a result, this study sets out to basis a ML approach that can predict the likelihood of a disease attack at an early stage by employing data from IoT devices honestly sensing environmental conditions in crop fields. The mechanism made use of IoT technology to gather and evaluate environmental conditions in crop fields, thus enabling to accurately forecast occurrence of blister blight (Exobasidiumvexans) in tea (Camellia sinensis) plants. Nidhi Kundu *et al.,* [6] strive to generate an enhanced structure called Intelligent and 'Automatic Data Collector and Classifier' by incorporating IoT technology and DL. This structure seamlessly gathers visual and parametric data from pearl millet fields in ICAR, Mysore, India. Gathered data is then automatically transmitted to both a cloud server and a Raspberry Pi. To precisely forecast blast and rust infections in pearl millet, scholars have examined 'Custom-Net' mechanism, which is exemplified on the cloud server and works in collaboration with Raspberry Pi. The study employs the Grad-CAM to effectual imagine extracted features by 'Custom-Net'. Additionally, study examines effect of transfer learning on both 'Custom-Net' and other popular mechanisms, like VGG-19, VGG-16, Inception-V3, ResNet-50, and Inception ResNet-V2. Through investigational outcome and feature visualization using Grad-CAM, observed that 'Custom-Net' effectively extracts relevant features, and transfer learning further enhances this procedure.

Jingyao Zhang *et al.,* [7] introduced a strategy to classifying cucumber leaf diseases in real-world environments by employing an incorporation of limited sample size and deep convolutional neural networks. Through a sophisticated two-stage segmentation mechanism, the researchers were able to extract lesion images from the cucumber leaves to use as training samples. To further enhance their model's performance, the team incorporated rotation and translation techniques and fed lesion images into an activation reconstruction GAN for data augmentation, resultant in generation of additional training samples. At last, by implementing a dilated and inception CNN trained on the augmented data, the authors were able to considerate enhance the accuracy of disease identification in cucumber leaves. Fazeel Ahmed Khan *et al.,* [8] examined farming by incorporating IoT technology into greenhouse operations. Through this innovation, small-scale greenhouses are transformed into conventional smart facilities. By incorporating automated systems, the team effectually monitors environmental conditions, manages irrigation, collects images through strategically installed cameras, and predicts diseases based on leaf datasets.

2. IoT System Model

IoT network typically contains small, connected devices, called IoT nodes, which send data to a central BS. The network also integrates cluster heads, which collect data from IoT nodes and forward it to the BS. In this context, the IoT consists of multiple sensor nodes designated as $k = \{k_1, k_{2,} ..., k_m, ..., k_h\}$, with h representing the overall amount of these nodes. In an IoT structure, each node acts as a BS that transmits data along optimal paths. The network interconnects various protocols to minimize power usage, like Zigbee, Z wave, and Bluetooth. Each protocol has unique characteristics for specific applications. Moreover, the IoT smart network mechanism integrates energy-based resources, managed by BSs within the network. System mechanism is stated in Figure 1. Data is processed and evaluated by a central system, like a computer, server, or cloud-based platform. The nodes are located over the simulation area and are equipped with the high specification cameras. The plant leaf images are sensed by the IoT nodes at frequent interval of time and thus, the data is collected in a database and are transferred to the destination using the proposed SEGOA for the further process, i.e., plant leaf disease detection.

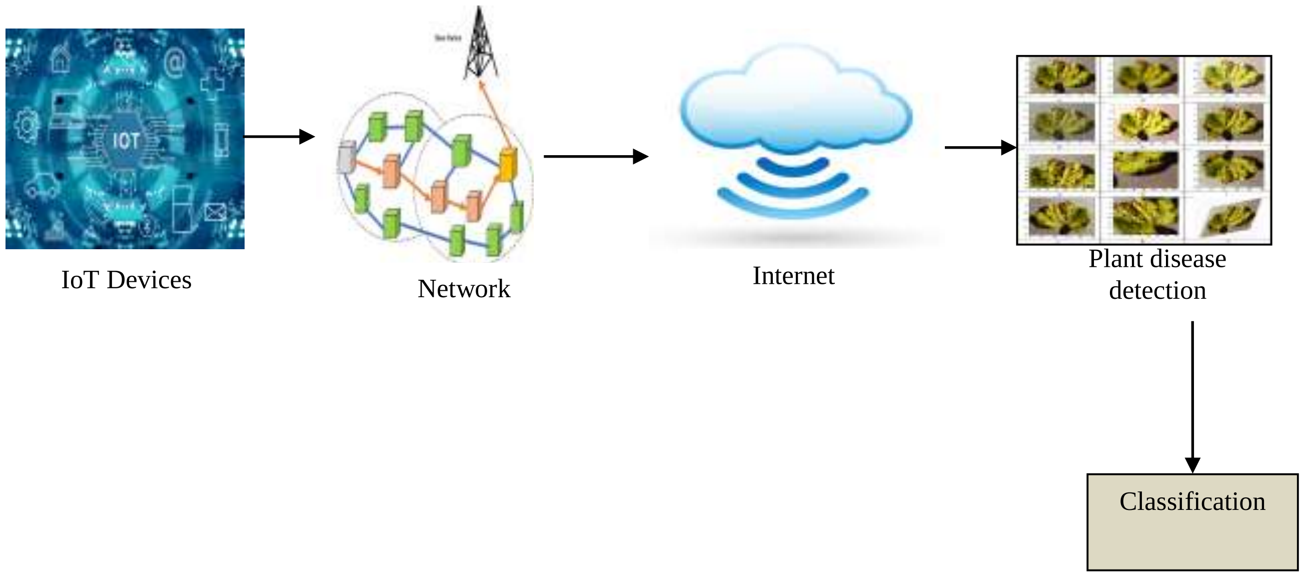


Figure 1: IoT system model.

2.1 Energy Model

This section evaluates the energy consumption by each node through packet transmission and defines the overall energy consumed by the entire network [16]. To evaluate the lifespan of the link based on remaining energy, the rate at which nodes deplete their energy is calculated:

$$Eg_R = \left(\frac{eg^r_{T_a} - eg^r_{T_{a+1}}}{T_a - T_{a+1}} \right) * \left(\frac{r_t + 1}{n} \right) \qquad (1)$$

where, $eg^r_{T_a}$ indicates obtainable energy of node at time T_a, r_t indicates count of overhaul per packet, and $eg^r_{T_{a+1}}$ signifies obtainable energy of node at time T_{a+1}.

3. Proposed Method

This segment presents a hybrid framework for DL in plant leaf identification. The framework integrates several steps: Input image undergo pre-processing to eradicate noise and unnecessary pixels employing a image resizing and median filter. After pre-processing, image is subjected to data augmentation techniques, such as brightness adjustment, zooming, shearing, flipping, and rotation. These techniques augment variety of dataset, improving mechanism performance [14]. At the onset, the simulation of IoT is initiated as the IoT nodes carry out the task of routing the sensed images of plant leaves. This is achieved through the innovative SEGOA, which is a modification of GOA [1] utilizing EWMA for improved performance. The procedure integrates CNN to extract RoI to pinpoint the diseased area on the leaves. Employing a hybrid network combining AlexNet [16] and ShuffleNet [15], referred to as AlexNet-ShuffleNet, the leaves are classified into healthy and unhealthy subclasses. The unhealthy classes of the images are further classified under three infectious subclasses, like bacterial, fungal, and viral. Figure 2 portrays architectural structure of presented methodology.

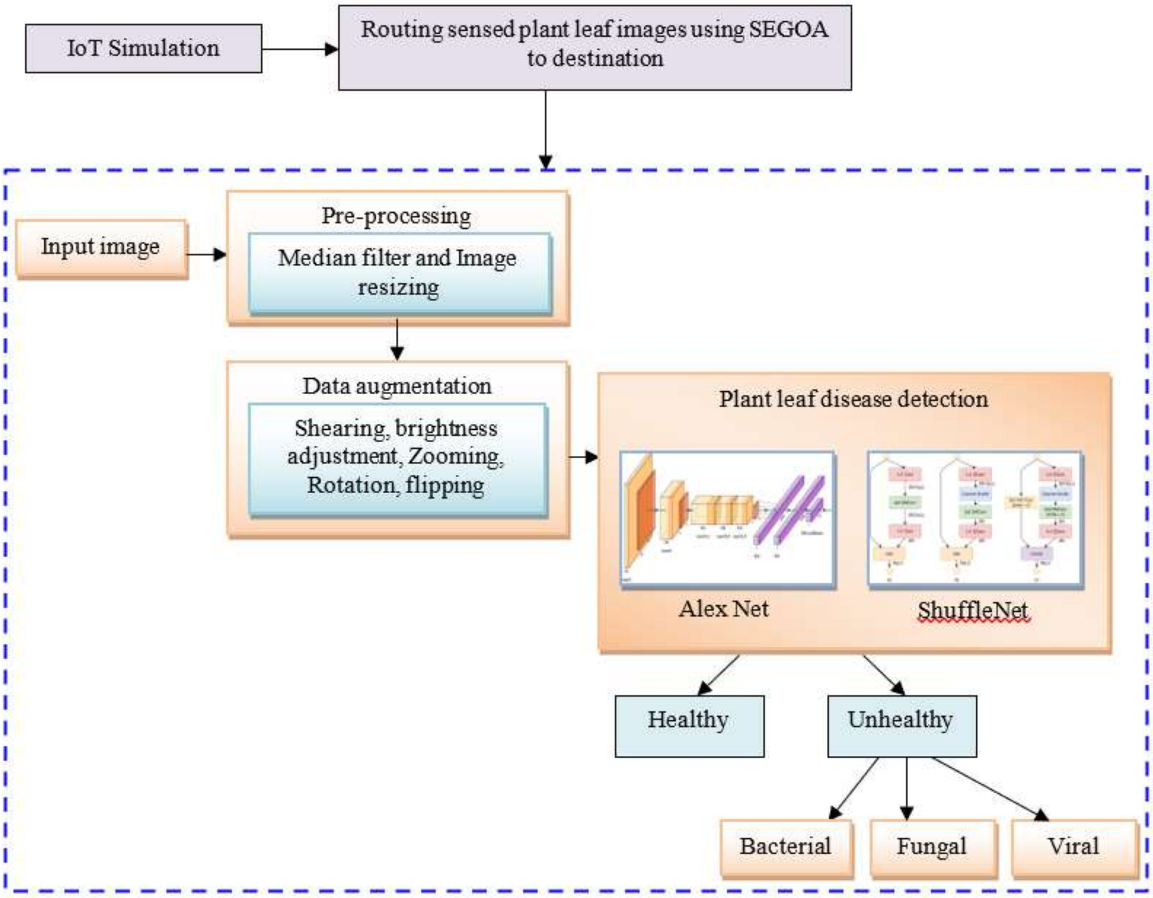


Figure 2: Architectural representation of proposed methodology

3.1 Routing using Serial Exponential Golf Optimization Algorithm

This segment illustrated the SEGOA mechanism, inspired by golf dynamics, for routing in plant leaf disease detection. The GOA algorithm, upon which SEGOA is based, employs two stages: exploitation and exploration. Advantage of GOA algorithm is that it has ability to resolve the global optimization and thus, it is employed considering routing as an optimization problem. GOA, a population-based approach, searches for optimal solutions by randomly allocates its members around the search space. Each member's location in this space corresponds to the rates of the variables in the optimization issues. Population of members might be mathematically stated as a matrix. The GOA algorithm is efficient in both exploration and exploitation phases, balancing both aspects well. It uses a random distribution of population members in problem space, same as to other metaheuristic algorithms. The serial exponential statistical mechanism is used to the GOA, conveying equal weights to all observations in the current time. This enhancement increases the GOA algorithm by elevating its speed to find answers and the quality of the solutions it finds. Furthermore, it needs less memory, building it practical for the utilization in optimization algorithms. As such, this alteration permits the GOA algorithm to execute optimization tasks more efficiently.

Step 1: Initialization

The GOA [27] defines the distribution of its members by employing a mathematical matrix eqn. (3). Like many search algorithms, each member starts in a random position within the problem's search space eqn. (4). These positions are uniformly distributed, sense they are extend out evenly around the space.

$$E = \begin{bmatrix} E_1 \\ \vdots \\ E_i \\ \vdots \\ E_n \end{bmatrix} = \begin{bmatrix} e_{1,1} & \cdots & e_{1,d} & \cdots e_{1,m} \\ \vdots & \ddots & \vdots & \iddots \vdots \\ e_{i,1} & \cdots & e_{i,d} & \cdots e_{i,m} \\ \cdots & \iddots & \vdots & \ddots \vdots \\ e_{n,1} & \cdots & e_{n,d} & \cdots \; e_{n,m} \end{bmatrix}_{n \times m} \quad (3)$$

$$E_i : e_{i,d} = l_d + rn \times \left(u_d - l_d\right) \quad (4)$$

where E is GOA population matrix, m is count of variables, n is count of GOA members $e_{i,d}$ is value of variable d^{th} symbolized by GOA member i^{th} whereas rn is a random count between 0 and 1, E_i is GOA member, and u_d and l_d is upper and lower bounds of variable d^{th}.

Each member of GOA is a possible solution to issue and affects problem variables. For each GOA member, the rate of objective function might be defined and stated in a vector (eqn. 5). According to this vector, the gained rate for objective function can be calculated.

$$f = \begin{bmatrix} f_1 \\ \vdots \\ f_i \\ \vdots \\ f_n \end{bmatrix}_{n\times 1} = \begin{bmatrix} f(E_1) \\ \vdots \\ f(E_i) \\ \vdots \\ f(E_n) \end{bmatrix}_{n\times 1} \qquad (5)$$

where, f denotes a vector of objective function rates. Each element f_i states the objective mechanism's accomplished value employing the i^{th} member of the GOA.

Step 2: Fitness function

In the objective function mechanism, member with finest value is measured optimal solution. As the locations of the GOA members change by each iteration, the objective function values are also restructured. Therefore, the optimal member might also be restructured in each iteration. Here, fitness function is designed based on the energy remaining in a node and the delay. Since the energy remained in the node has to be maximized and the delay has to be in minimum, the fitness is considered as a minimum function.

$$f = \frac{(1 - Eg_R^i + D^i)}{N} \qquad (6)$$

where, N represents the normalization factor, Eg_R^i is the energy remained in i th node and D^i is the delay (total count of nodes in a path).

Step 3: Exploration:

In golf, first swing is performed in area of golf course called grip. Golfers aim to make the better possible shot towards the hole with their first swing. To do this, the initial swing is simulated, and a new location is assessed for each player (called a "GOA member") employing (6). If the findings of this simulation improve the player's score, the new position is employed to rearrange the player's preceding position according to eqn. (7). In golf, shots can either land past the hole or approach it. The parameter *i* in the eqn (3) impersonates this state. When *i* equals 1, the ball approaches the hole. To enhance the algorithm's global search capability, when *i* equals 2, the probability of moving the ball is elevated, letting the algorithm to discover a wider range of areas in the search space.

$$E_i : e_{i,d} = lh_d + r \times (mh_d - lh_d) \qquad (7)$$

$$E_i = \begin{cases} E_i^{p1}, f_i^{p1} < f_i \\ E_i, else \end{cases} \qquad (8)$$

where, f_i^{p1} states its rate of objective mechanism, E_i^{p1} denotes a latest computed spot of i^{th} GOA member according to phase of exploration, rn defines random count with the intervel [0−1], $E_{i,d}^{p1}$ denotes its d^{th} dimension, B signifies GOA finest member, B_d exemplifies its d^{th} dimension, and p states a arbitrary count that is selected randomly from set of {1,2}.

Step 4: Exploitation:

The area around the hole on a golf course is selected as the "green." Players take shots known as "putts" on the green with minimal force to direct the golf ball into hole. These low-energy shots assist to keep the ball in the green area. In the GOA, each personal symbolizes a probable answer to an optimization problem. The green area corresponds to a region where every personal is examined to detect potential areas for enhancement. The GOA algorithm updates the positions of its individuals based on these examinations. For each individual, a new location is defined according to the mathematics of a golf putt. If this new location enhances objective function value, it reinstates individual's prior location.

$$E^{t+1} = E^{t} + (1-2r) * \frac{lh_d + r + (uh_d - lh_d)}{t} \tag{9}$$

where, E is population matrix of GOA, E_i is j th GOA member, $e_{j,d}$ is rate of d th variable by j th GOA member, r is a random count in interval $[0-1]$, and lh_d and mb_d are lower bound and upper bound of d th variable.

For the purpose to elevate efficacy of the GOA algorithm [27], a concept, named serial exponential weighted moving average algorithm, is integrated to improve the performance of GOA further. The update equation in EWMA is represented as,

$$E_A^t = \beta * E^t + (1-\beta) * E_A^{t-1} \tag{10}$$

where, β is the weight , t is the iteration count and E_A^{t-1} is the outcome from previous iteration using EWMA. Rewriting the above eqn. in older weight till $(t-2)$ th period, it forms the serial EWMA as follows,

$$E_A^t = \beta * E^t + (1-\beta) * (\beta + E^{t-1} + (1-\beta) + (\beta + E^{t-2} + (1-\beta) * E_A^{t-3})) \tag{11}$$

$$E^t = \frac{1}{\beta} * \left\{ E_A^t - (1-\beta) + \left[\beta + E^{t-1} + (1-\beta) * (\beta * E^{t-2} + (1-\beta) * E_A^{t-3}) \right] \right\} \tag{12}$$

Assuming, the solutions in both EWMA and GOA are equivalent at the current iteration, eqn. (12) is substituted in eqn. (7),

$$E^{t+1} = \frac{1}{\beta} * \left\{ E_A^t - (1-\beta) + \left[\beta + E^{t-1} + (1-\beta) * (\beta * E^{t-2} + (1-\beta) * E_A^{t-3}) \right] \right\} + (1-2r) * \frac{lh_d + r + (uh_d - lh_d)}{t} \tag{13}$$

Step 4: Termination: After modifying the fitness solution, its quality is evaluated. Then, the steps from the second step are executed repeatedly. This iterative procedure continues until the best optimal solution is gained. The flowchart of SEGOA is stated in figure 3

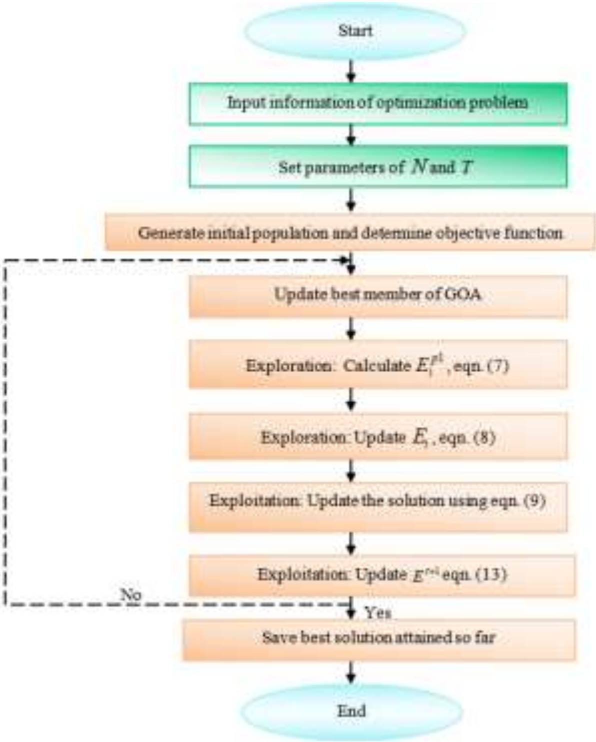


Figure 3: Flowchart of SEGOA

3.2 Plant disease and infectious classification using hybrid AlexNet-ShuffleNet

Following segment specifies the plant disease recognition and classification by employing sensed images routed via the proposed SEGOA. Pre-processing process is executed utilizing image resizing [27], median filter [28]. Data augmentation is executed afterwards. The plant leaves are classified as healthy and diseased subclasses using the optimized AlexNet-ShuffleNet, where the AlexNet-ShuffleNet framework. Moreover, the disease types are classified further into fungal/bacterial/viral infection using the AlexNet-ShuffleNet.

3.2.1 Preprocessing

Before data analyzing, it's important to preprocess it. The procedure contains cleaning, transforming, and structuring it to make it easy for use. Preprocessing approaches make sure the data is organized and suitable for modeling or evaluation.

Image Resizing

For image processing, size of an image is the main feature in examining ML performance. Large images enhance complexity of the mechanism and training time. In computer visualization, such as object recognition, images are often resized as a preprocessing step. This rescaling to a standard size simplifies algorithms and promotes consistent input data. For example, leaf images were resized to 32x32 pixels.

Median Filter: The median filter, commonly called order-statistics filter, replaces each pixel's value in an image with the median grayscale value from the surrounding pixels.

$$\hat{F}(h,Q) = \underset{z,W \in z_{h,Q}}{median}\{G(z,W)\} \tag{8}$$

Let $z_{h,Q}$ denotes an assortment of coordinates contained by a rectangular sub-image situated at a specified point (h,Q). The median of an image is evaluated by employing a unique pixel rate. Median filters are effective at removing specific kind of noise, particularly arbitrary noise, while introducing less blurring incorporated to linear filters of similar size. They are greatly valued for their noise reduction capabilities.

3.2.2 Data Augmentation

Data augmentation [23] integrates enhancing a dataset's size by generating variations of accessible data. This allows mechanism to become more robust and detect patterns that may not be present in original dataset. Data augmentation improves ML strategies accuracy for image datasets. Several mechanisms can be utilized to generate data variations, preventing overfitting by the strategy. Data augmentation is usually aided for image classification. It helps evade overfitting and boosts the mechanism’s accuracy. Transformations, like rotating, distorting, flipping, zooming, and adjusting brightness, are employed to original images. Rotating images at changing angles elevate the strategy’s ability to hold variations in object orientation, leading to enhanced generalization. Image manipulation mechanisms, like shearing (horizontally or vertically) assist the strategy adjust to patterns and covenant with misrepresentations. Zooming in and out imitates scale variations, improving performance on images taken from diverse distances. Horizontal or vertical flipping shows orientation changes, elevating the strategy’s ability to detect the same disease in several image orientations. Adjusting brightness simulates changing light, making the mechanism more adaptable to diverse illuminating conditions. Transformations like rotation, scaling, and shearing make images appear substantially diverse, evaluating the dataset and challenging the strategy. Moreover, image flipping and brightness arrangements can create new images, additional enriching the dataset.

3.2.3 Detection of plant leaf disease by Hybrid AlexNet-ShuffleNet

The research put forward an approach to identifying plant diseases by combining two established DL models: AlexNet and ShuffleNet. Resulting hybrid mechanism, known as AlexNet-ShuffleNet, delved to capitalize on unique strengths of each architecture to enhance precision and speed of disease recognition.

AlexNet

AlexNet [26], a neural network with 650,000 neurons and 60 million parameters, was revolutionary in examining an elevated activation function. Conventional neural networks relied on inadequate activation functions, like arctan, tanh, or logistic functions for non-linearity. But these functions display steep gradient rates only for inputs close to zero, important to the "vanishing gradient" problem. To contest this, AlexNet utilized the ReLU activation function. ReLU assigns a constant gradient of 1 for inputs above zero, which speeds up the training procedure. ReLU function might be exemplified through equation below:

$$w = \max(0, x_1) \tag{9}$$

This network integrates smaller sub-networks, with each prone to overfitting. Using an image i of height A and width B, convolutional layers mechanically extract features that are then compressed by pooling layer. The convolutional kernel, notated as j with height V and width C, performs convolution operation:

$$C(A,B)=(j*P)(A,B)=\sum_{U}\sum_{V} j(A-V,B-C)\,j(V,C) \tag{10}$$

Mechanism employs a CNN to extort features from images. It shares parameters to diminish its complexity. Pooling layers are employed to additional compress extracted features. To enhance feature representation, the mechanism utilizes cross-channel normalization, a local normalization mechanism. Before giving feature maps to subsequent layers, they are normalized. Classification is executed in fully connected layers by employing Softmax activation function, which is considered utilizing eqn. below:

$$soft\max(x)_I=\frac{\exp(x_I)}{\sum_{J=1}^{M}\exp(x_J)} \quad \text{for } I=0,1,2,\ldots,k \tag{11}$$

ShuffleNet

ShuffleNet [18] uses "group convolution" instead of "point convolution" to elevate accuracy. In group convolution, each group's output depends solely on its inputs, isolating details among groups. To optimize efficiency, ShuffleNet employs "pointwise group convolution," " shuffling," and " depth wise convolution " mechanism. Furthermore, BN strategy makes sure of constant data format and the subsequent layers despite network weight adjustments. This facilitates greater learning rates and lesser dropouts to be employed. To attain normalization, each dimension of d-dimensional data $Y=Y^{(1)},Y^{(2)},\ldots,Y^{(P)}$ is normalized by utilizing eqn. (12). This equation integrates per-dimension variance and mean of data designated by g and var. Subsequent function of BN, eqn. (13) states ReLU activation function.

$$\tilde{Y}^{(K)}=\frac{Y^{(K)}-g[Y^{(K)}]}{\sqrt{\mathrm{var}[Y^{(K)}]}} \tag{12}$$

$$\mathrm{Re}LU(Y)=\begin{cases}0, & if\ Y\le 0\\ Y & otherwise\end{cases} \tag{13}$$

In eqn. (13), Y symbolize function's input, and its output is zero for negative rates and Y for positive values. Let X_1 be output yielded by AlexNet, indicated as $soft\max(x)_I$, and X_2 output obtained from ShuffleNet, which is

$$X_2=\sum\sum Y^{(K)}*Q_i*X_i \tag{14}$$

Calculated output layer attained from merging layer,

$$X_3=\sum_{d}\sum_{z} Z_{t+1}*X_2*\vartheta \tag{15}$$

where, ϑ stated weight ranges from (0-1) and Z_{t+1} denotes the augmented images, considered as the features.

3.3 Dataset description

To execute the experiment employing the AlexNet-ShuffleNet mechanism, five datasets were utilized: grape dataset [10], rice leaf dataset [11], sugarcane disease dataset [12], black gram plant leaf disease dataset [13] and dataset of tomato leaves [14]. For the infectious classification task, experts manually classified all diseased samples in these datasets into fungal, viral, and bacterial classes to ensure accurate evaluation.

Apple Dataset [10]: Apple disease dataset consist of different infectious apple leaves images. It has four categories: apple scab (630 images), apple black rot (321 images), apple cedar apple rust (275 images), and healthy apple leaves (1645 images).
Rice Leaf Diseases Dataset [11]: A database of 120 high-quality JPEG images is attained for scholars seeking efficient data for their examination on rice leaf diseases. The dataset categorizes the images into three different disease kinds, with each category including 40 images.
Sugarcane Disease Dataset [12]: This dataset is a helpful tool for enhancing and testing machine learning algorithms designed to classify and count sugarcane stalks. It contains 300 images categorized into three types.
The Blackgram Plant Leaf Disease [13] Dataset encompasses an exclusive collection of 1000 high-quality images. These images are categorized into five different groups, containing the spectrum of leaf diseases that affect Blackgram crops. The dataset contains images showing Powdery Mildew, Yellow Mosaic, Leaf Crinkle, Anthracnose, and images of healthy leave for comparison.
The Tomato Leaves Dataset [14] includes two sets of images featuring tomato leaves from several sources. It contains 14,531 images, each depicting an isolated tomato leaf on a background. To improve the dataset, redundant categories were evaluated, and the image dimensions were attuned from 256x256 to 227x227. Furthermore, five subsets were generating utilizing 5-fold cross-validation to enhance the dataset's effectiveness.

4. Results

This part of the work states the outcomes and evaluations of AlexNet-ShuffleNet method for recognizing plant infections in the context of IoT. The research implemented this approach employing Python. Work carefully signifies findings in a logical method alongside several visual aids, like tables, graphs, and charts. This confirms that findings are presented clearly and comprehensively for easy understanding.

5.1 Performance Metrics

For the purpose to evaluate efficacy of the mechanism in classification, several performance metrics are employed.

a) Accuracy: This metrics, gauges mechanism's performance by evaluating the percentage of predictions that it makes accurately. To exanimate accuracy, overall amount of accurate predictions is separated by overall count of predictions made.

b) Sensitivity: Sensitivity measures how well a test can classify actual positive cases. It is calculated by separating count of true positives (cases that are correctly accredited as positive) by overall count of actual positive cases.

c) Specificity: This measurement examines how well an approach can accurately identify negative cases. It is evaluated by dividing count of cases accurately documented as negative (true negatives) by overall count of true negative cases.

5.2 Performance Analysis

The performance analysis based on varying training data and varying K-fold of proposed methodology is executed in following sector.

5.2.1 Energy:

Figure 4 illustrates the energy graph of the proposed SEGOA for different iterations. The proposed strategy stated that when iteration increases the network energy also increases while the network energy diminishes when the number of rounds increases. The proposed SEGOA had the network energy of 0.654 J for an iteration of 60 and 1000 rounds. At 600 rounds and 80th iteration, the presented mechanism attained the network energy of 0.791 J. For the iteration of 100 and 1000 rounds the proposed strategy attained network energy of 0.666 J.

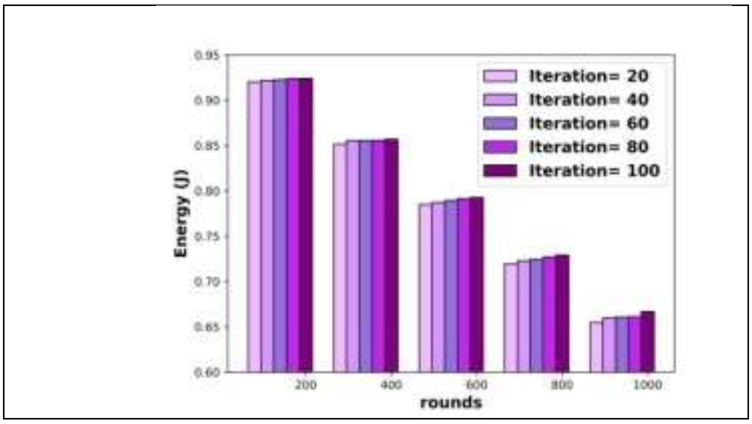
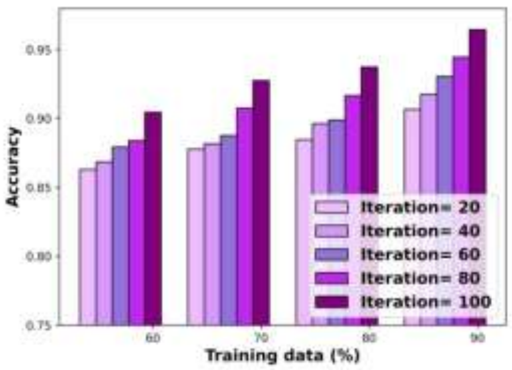


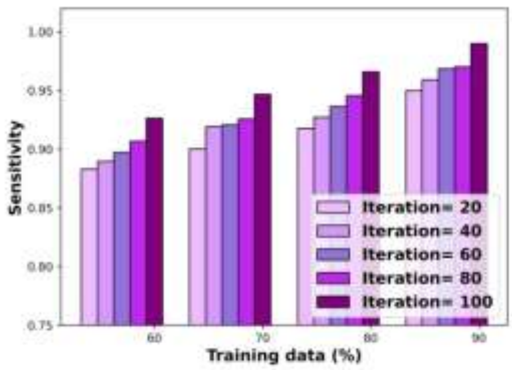
Figure 4: Energy Consumption

5.2.2 Varying Training data

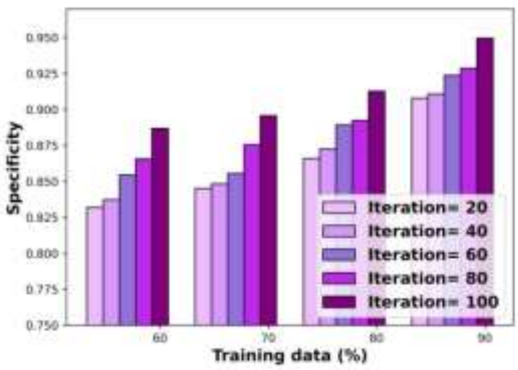
The suggested strategy examined performance evaluation with the assistance of metrics, like specificity, sensitivity and accuracy for the detection of plant leave infection. The performance examination outcome are shown in Figure 5. In Figure 5(a), see that accuracy increases up to 0.937 for 100 iteration and 80% of training data was exploited. However, accuracy was only 0.904 for same iteration when only 60% of the training data was exploited. Figure 5(b) states evaluation based on sensitivity, for that at the iteration of 100 and training data of 90% the suggested mechanism gained a sensitivity of 0.989. The proposed mechanism accomplished sensitivity of 0.936 for iteration of 60 and training data of 80%. Figure 5 (c) stats evaluation based on specificity, where presented mechanism gained a specificity of 0.848 for training data of 70% and an iteration of 40. The presented evaluation states that the performance metrics has proven the efficacy of combined AlexNet-ShuffleNet mechanism in categorizing plant disorders.



(a)



(b)

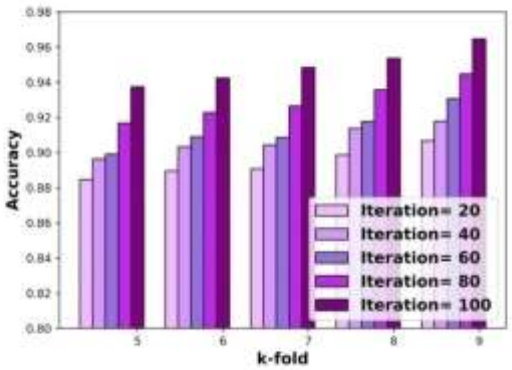


(c)

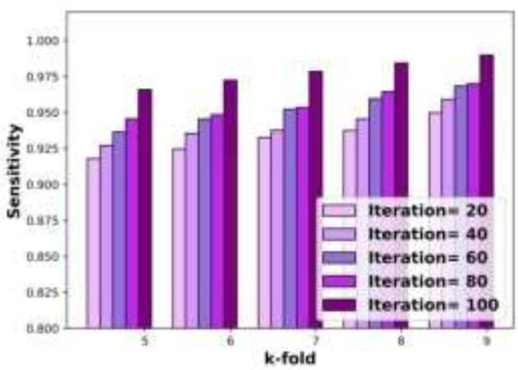
Figure 5: Performance examination of adopted mechanism with training data, (a) accuracy, (b) sensitivity, and (c) specificity

5.2.3 Varying K-fold

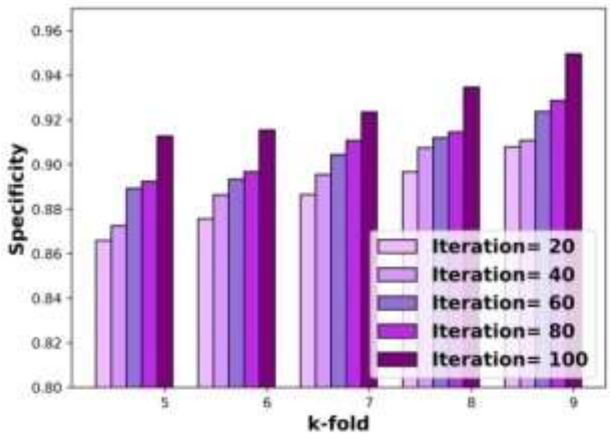
Figure 6 estimates accuracy of proposed strategy employing k-fold cross-validation. Figure 6(a) shows that Hybrid AlexNet-ShuffleNet procedure reached an accuracy of 0.964 with k-fold of 9 at iteration 100, stating its greater accuracy in diagnosing plant diseases. Figure 6(b) analyzes sensitivity, integrating that presented mechanism achieved a sensitivity of 0.952 with k-fold of 7 at iteration 60, effectually detecting diseases in plants. Figure 6(c) shows that AlexNet-ShuffleNet mechanism is highly specific, achieving a specificity of 0.978 for K-fold cross-validation of 7 and an iteration of 100. The findings stated efficacy of the adopted strategy.



(a)



(b)



(e)

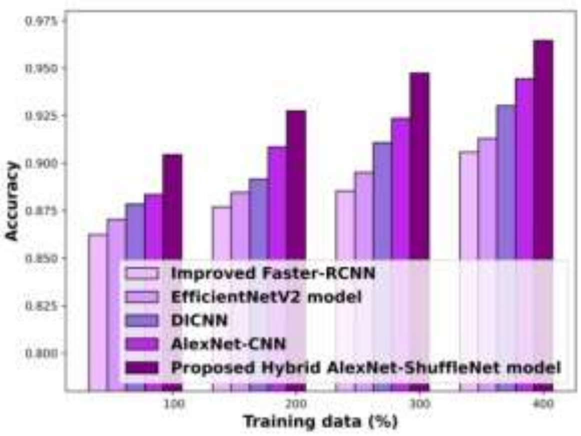
Figure 6: Performance assessment of the presented strategy with K-fold, (a) accuracy (b) sensitivity (c) specificity, (d) energy.

5.3 Comparative Analysis

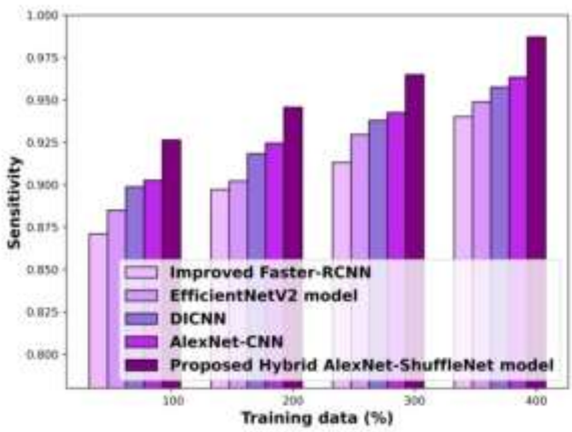
The presented mechanism was compared to other traditional mechanism, like Improved Faster-RCNN [2], EfficientNetV2 model [4], DICNN [7], and AlexNet-CNN [8].

5.3.1 Training Data

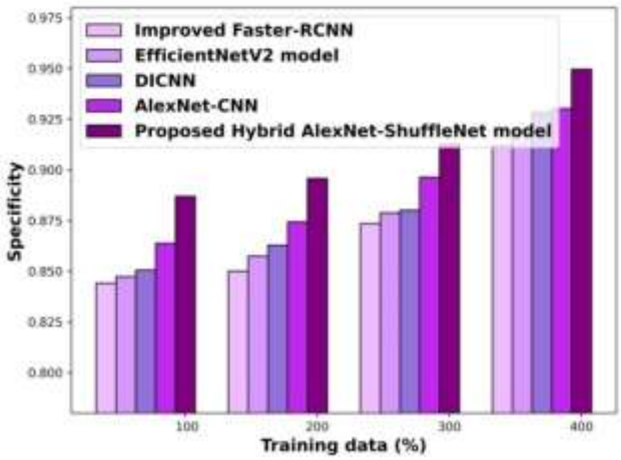
Figure 7 comprises performance evaluation of proposed strategy with other conventional approaches like, EfficientNetV2, DICNN, Improved Faster-RCNN, and AlexNet-CNN. When trained with 60% of the data, AlexNet-ShuffleNet attained an accuracy of 0.904, surpassing the other mechanisms which is, Improved Faster-RCNN (0.862), EfficientNetV2 (0.870), DICNN (0.878), and AlexNet-CNN (0.883) is illustrated in figure 7 (a). Figure 7(b) states sensitivity of suggested mechanism. The AlexNet-ShuffleNet strategy excels, achieving a sensitivity rate of 0.964 with 80% training data. In contrast, the DICNN and AlexNet-CNN methods have sensitivity rates of 0.937 and 0.942. Figure 7(c) evaluates specificity. The adopted mechanism outperforms other approaches, obtaining a specificity rate of 0.949 with 90% training data. This surpasses specificity rates of 0.912 and 0.919 attained by Improved Faster-RCNN and EfficientNetV2 strategy.



(a)



(b)

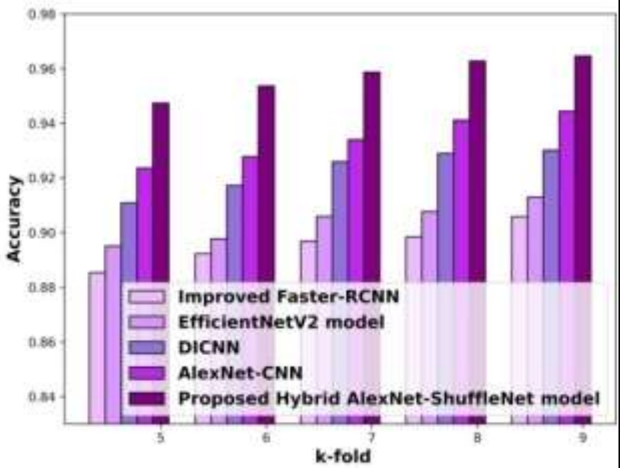


(c)

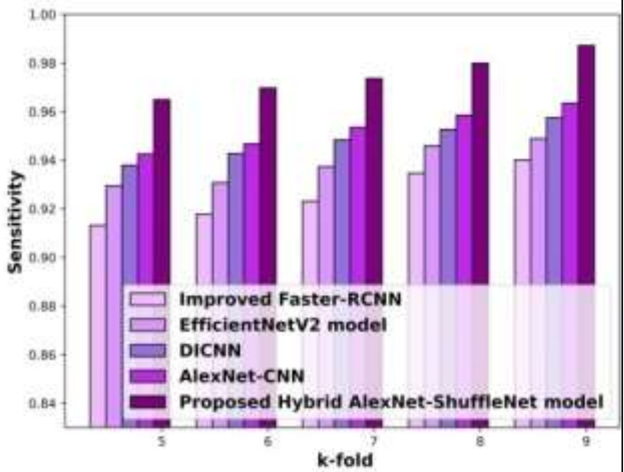
Figure 7: Comparative examination of mechanism with training data a) accuracy b) sensitivity c) specificity

5.3.2 K-fold

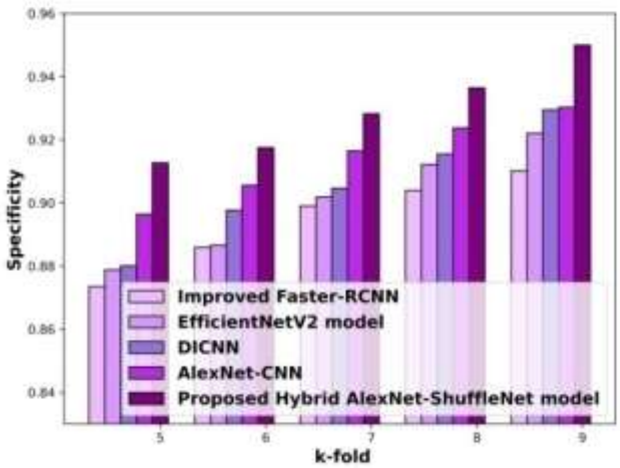
Proposed mechanism was evaluated against traditional approaches exploited k-fold cross-validation is exemplified in Figure 8. Findings states that suggested mechanism outshines EfficientNetV2, CNN, and Improved Faster-RCNN models in terms of sensitivity, specificity, and accuracy. In Figure 8(a), suggested mechanism gained an accuracy score of 0.953 for a k-fold value of 6, outperforming the accuracy of the other mechanisms. Figure 8(b) defines the efficacy of Hybrid AlexNet-SuffleNet mechanism in terms of sensitivity, with a score of 0.973 for a k-fold value of 7. This exceeds sensitivity values of DICNN and AlexNet-CNN models, which are 0.948 and 0.953. Figure 8(c) exemplifies the proposed method outperformed other techniques in terms of specificity. With a k-fold value of 9, presented strategy attained a specificity of 0.949, significantly higher than Improved Faster-RCNN (0.910) and EfficientNetV2 (0.922).



(a)



(b)



(c)

Figure 8: Comparative measurement of techniques with k fold (a) accuracy (b) sensitivity (c) specificity

Table 1 exemplifies how well AlexNet-ShuffleNet model performs when compares to other conventional mechanisms. Incorporated to Improved Faster-RCNN, AlexNet-ShuffleNet was 6.12% more accurate. It was also 5.39% more precise than the EfficientNetV2 model. When contrasted with EfficientNetV2 strategy, it was 3.95% more in sensitivity. And when contrasted to DCINN, it was 2.21% more in specificity. These results show that presented AlexNet-ShuffleNet accomplishes better than other mechanisms, making it a promising approach for improving accuracy, sensitivity, and specificity in infectious plant leaf image classification tasks.

Table 1: Comparative discussion

Metrics	Improved Faster-RCNN	EfficientNetV2	DCINN	AlexNet-CNN	Proposed Hybrid AlexNet-ShuffleNet model
Accuracy	0.905	0.912	0.930	0.944	**0.964**
Sensitivity	0.940	0.948	0.957	0.963	**0.987**
Specificity	0.912	0.919	0.928	0.930	**0.949**

5. Conclusion

In recent years, IoT devices have become amazingly popular, by giving valued assistance in several applications. In agriculture, automated plant disease identification technologies offer various benefits but also present potential challenges. Work suggests, an IoT-based plant disease mechanism has been initiated to assist the agriculture platform. First, IoT simulations is executed, where sensors capture images of plant leaves and broadcast them to a central location for disease identification. The transmission procedure is optimized utilizing a newly adopted algorithm, named SEGOA. SEGOA modifies the GOA by integrating EWMA to elevate the routing performance. After the data transfer, AlexNet-ShuffleNet was used to perform the disease detection and infectious classification of plant leaves. The research findings demonstrate that this innovative approach gained maximum accuracy rate of 96.4%, sensitivity rate of 98.7% and specificity rate of 94.9%. Presented approach can significantly enhance agricultural practices by enabling early identification and prevention of infectious leaves issues in plants.

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