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IOT with Cloud based Smart Farming for Citrus Fruit Disease Classification using Optimized Convolutional Neural Networks

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ABSTRACT: In India, agriculture is considered as a main source of income and more than 60% of people are linked to agriculture. With the advances in recent technologies, Smart farming allows to utilize Internet of things (IoT) to assist the farmers for reducing the wastages and improving the productivity. At the same time, Citrus is a main source for vitamin C and gets affected by citrus diseases that spoil the fruit quality. In this paper, an IoT based Smart Farming model is presented by the use of improved particle swarm optimization (IPSO) based multilevel parameter optimized feature selection algorithm for convolutional neural network (CNN) classifier named as IPSO-CNN technique. The proposed method initially captures the plant images using IoT devices and stores the data in cloud. The proposed IPSO-CNN model gets executed on the cloud to identify and classify the presence of plant diseases. For experimentation, a benchmark citrus fruits image dataset named Citrus Image Gallery dataset is employed. Simulation outcomes demonstrate that IPSO-CNN has the capability to manage, optimize and uncertainty with improved classifier accuracy even though decreased the number of features.

Keywords: Citrus, Plant disease, Smart farming, IoT, Deep learning.

Abbreviations: IoT, Internet of Things; IPSO, Improved Particle Swarm Optimization; CNN, Convolutional Neural Network; GA, Genetic Algorithm; RGA, Region Growing Algorithm; AUC, Area Under Curve; SVM, Support Vector Machine; K-NN, K-Nearest Neighbour Algorithm; LDA, Linear Discriminant Analysis.

I. INTRODUCTION

Generally, India is known to be the land of agriculture farming. Most of the peoples are depending agriculture as main source of survival in global. Agriculture is said to be the fundamental source for economic growth of India. It offers several chances for two-third of people in and around the world. Additionally, the health status of a plant is very significant that helps many farmers to gain profit. In order to prevent many types of plant disease, the plants must be observed regularly interms of plant health which is a significant portion of agriculture. If there is presence of pests and insects then, plants might get affected which leads in decreased crop yield. The earlier plant observing would be performed with naked eye that consumes maximum duration. Therefore, automated prediction technique should be obtained to detect the plant infection at primary stages. Thus, different types of disease controlling procedures are applied by farmers to periodically protect plant from disease attacks respectively.

Here, Internet of Things (IoT) has been proposed which defines the connection of external devices, transports, home devices, and alternate goods that are combined with appliances, software, detectors, actuators, and network that enable them to link and interchange the information by providing chances for straightforward integration of physical world to systems that results in minimized human contribution. As the study states that, in the year 2050 a global population would be attained as 9.6 billion. Thus, the population could be adopted by the evolution of IoT in farming application. In future decades, demand for food would be faced with the problems of intense weather state as well as eradication of farmers. By introducing intelligent farming along with IoT tends to improve crop cultivation in agriculture domain. The disease management process is an essential source of every farmers as well as agricultural professionals. The presented model focuses mainly in detecting the plant disease with the application of IoT technique. In several plants disease intrusion could be identified by testing plant leaves. Therefore, the projected study reveals the prediction of plant disease that exists on plant leaf. Here, difference between the normal and diseased leaf could be found on the basis of modification of temperature, humidity as well as colour. Thus, the upcoming research has been provided with various parameters to know applications used.

Seelye *et al.*, (2011) has proposed cheaper colour sensors to monitor the development of a plant in a laboratory [1]. The automatic system is applied to observe the leaf colour which states the health condition of a plant. A new technique has been presented to identify the insects or pests by automated system and to divide the plant under the application of image processing method [2]. Therefore, the evolved model aims to minimize the processing time and pest forecasting which is used for farming environment rather to be used in green house plantation. In addition, there is a major pest threat named whitefly, a bio-aggressor that reduces risk for all crops and plants has been assigned as pest of interest in this study.

Also, it is sampled for various whiteflies that affect diverse types of leaves that provide the accuracy of 98% of whitefly detection has been obtained. A pest control model is deployed for planting crops with the help of image processing models in MATLAB. The images are again induced to various stages as Pre-processing, Transformation and clustering [3].
Consequently, Jha *et al.*, (2019) signified as IoT Implementation of wireless monitoring for agricultural features [4]. The wireless system has been designed for observing the environmental status in farming field such as temperature, soil pH, soil moisture as well as humidity apart from detecting leaf disease. An IoT application is introduced for the purpose of detecting disease of plant and presence of insect pests [5]. Hence, IoT framework is applied for gathering data about the disease which often occurs in plants are predicted with the help of sensor nodes, data computation, data mining, and so on. Apparently, a micro-controller based auto-irrigation and insect prediction can be performed by applying image processing approach [6]. Furthermore, models of image diagnosis are used in agriculture to offer effective protection to crops that leads in maximum crop growth as well as better yield.
Additionally, a pest controlling system is proposed to acquire maximum accuracy in farming by the use of IoT [7]. Many farmers cultivate sugarcane from India due to the presence of bugs and pests there is no maximum yield in crops. However, the presented models applied an arduino to monitor the noise as well as temperature. Sai *et al.*, (2017) specified an arduino on the basis of pest managing with the help of real time monitoring sensors to detect the bugs present [8]. Moreover, this study attempts to design a robot which must be capable to perform the allocation of pest control agents, obstacle elimination of self-guidance in the field with no presence of user interference as well as to form a clean platform to attain better cultivation of crops which has been monitored from closed atmosphere. Then, Schmittmann and Schulze Lammers (2017) employed a true-color sensor which is applicable in estimating the type of plant [9]. Moreover, system designed is dependent on free cascading true-colour sensors in real time analysis and finds a single weed as well as crop that applies arithmetic technique and decision methods.
Chuanlei *et al.*, (2017) projected an apple leaf disease exploration with the help of Genetic Algorithm (GA) and correlation which are termed as feature selection techniques [10]. Therefore, colour modification for input RGB (Red, Green and Blue) image has been developed initially as well as RGB method is transformed as HSI (Hue, Saturation and Intensity), YUV and gray methods. Here, background might be eliminated and disease affected image would be classified along with Region Growing Algorithm (RGA). Subsequently, the diseases may be analyzed under the application of SVM classification model. An execution of IoT takes place, including image processing for plant growth managing system [11]. Finally, these works concatenate image processing with IoT model for observing the plant that tends to gather ecological aspects like moisture, temperature and so on. Recently, deep learning models are also been utilized [12, 13].

In this paper, an IoT based Smart Farming models are presented by the use of improved particle swarm optimization (IPSO) dependent multilevel parameter optimization feature selection technique to Convolutional Neural Network (CNN) classifier named as IPSO-CNN technique. The proposed method initially captures the plant images using IoT devices and stores the data in cloud. The proposed IPSO-CNN model gets executed on the cloud to identify and classify the presence of plant disease. For experimentation, a benchmark citrus image dataset named Citrus Image Gallery dataset is employed. Simulation outcomes display that IPSO-CNN has the ability to manage optimize and uncertainty through enhanced classifier accuracy although decreased the number of features.

II. THE PROPOSED METHODS

The overall methods presented in the model is revealed in Fig. 1. As shown in figure, the citrus images are initially captured from the farming land by the use of camera sensors which captures the leaves and fruits of citrus. Then, it is connected to an IoT device named Rasbperry Pi3 which receives the image and transmits it to the cloud Thingspeak platform. Then, the training and testing of images takes place by the use of IPSO-CNN model. Once the model has been trained, a new input test image can be given to determine the defected portion of the image along with its class label.

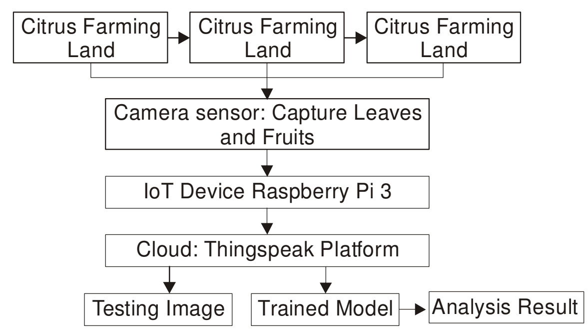

Fig. 1. Process involved in IPSO-CNN model.

The presented techniques obtain from input attributes transmitted to issue in question, namely the trained information that would be utilized with attributes transmitted to the CNN structures that would be generated, namely the particles' most number of layers in initialized. The presented technique, the gbest particle can be dependent on the optimal blocks initiate in the swarm with pursuing the IPSO technique. However, there is no requiring for manually optimization the attributes of every block. We presented manner, the attribute optimize does not start over. Optimal blocks are accepted together subsequently creation in the type of gbest particle. Presently, the particle only estimate that requires to be resumed at all iteration, although the technique make sure that optimal blocks are reserved. Then presented technique contains the IPSO structure, containing six processes that permitted for utilizing to explore the best CNN designs: a capable CNN demonstration, to initialize swarm particles, fitness estimation of separate particles, to evaluate the various operation between two particles, velocity calculation with particles are also performed.

A. CNN representation

Illustration is the most essential feature if planning a technique that manages difficult formations, namely CNN designs. They present a direct encoded system for CNN structures. Whenever the CNN is utilized to trained, testing or estimation, the method is executed subsequently an array including the aspects of every layer in the particle. The presented technique only explores CNN structures. The weights of every layer are not measurable, searchable or evolvable in the present study. The four varieties of layers: conv, average pooling, FC and max pooling. Every position in the record of layers has the data considering its variety and hyper-parameters. For instance, a single location in these lists will have the layer variety, if the number of outcome feature maps, when conv or the number of neurons, if FC with kernel size, when Conv/Pool. Fig. 1 shows the demonstration utilized in the IPSOCNN technique, where C, P and FC represent conv, pooling, and FC layers, correspondingly. One of the essential feature of the technique is that the particle is utilized IPSO without require to change their data to numerical values. Still, the proposed is illustrate, every particle could be consideration as the range of functional blocks that can permit to utilize of custom blocks. Presently, the blocks utilized to present IPSOCNN are the 4 layers varieties illustrated before.

B. Initialization of the swarm

Initialize Swarm() is the initial phase in the presented IPSOCNN. In the operation would generate N particles by arbitrary CNN structures, and it is explained in Algorithm 2. Every particle will contain an arbitrary number of layers (C, P, FC layers) up to lmax. For creation possible CNN structures, the initial and end layer of each particle is always a convolutional with FC layer, correspondingly. Additionally, FC layers could be placed among convs layers, also only at the last of structure. Thus, during initialization, the technique requires to ensure that once an FC layer is further to structure, each layer subsequent to it is also an FC layer. Utilization of FC layers at the last of a CNN is a meeting implemented with other explorers in the domain. Usually, FC layers are utilized for classification and the features removed with Conv/Pool layers. Utilizing FC layers among Conv/Pool layers will improve the number of attributes of the overall CNN. These come from the details which is behind every pooling layer the numbers of outcomes are decreased with factor of 2. Following a certain number of pooling layers, the outcomes would be tiny sufficient to be utilized as input to the FC layers without requiring to utilize a group of neurons.

C. Fitness assessment

The fitness estimations are executed with function Compute Loss(). It is complete with executing the particle structure into a full-fledged CNN which is trained to full of train epochs. The estimation itself is completed with evaluating the loss function of every particle in the cross entropy loss. So, the objectives of the techniques are to find particle structure by least failure, considering the number of attributes or other criterion. Training is executed by utilizing Adam. Still, it is also feasible to added failure and batch normalized among layers removing the over fitting problem. The major blockage of the presented technique as each one of the N particles requires being prepared in the whole data set.

D. Determining variation among particles

In every single particle to initiate to calculating the velocity, we are required to specify how to evaluate the variation between two particles. In the outline of the process two particles P1 and P2, exposed in the top left corner is evaluated. For removing finish up by FC layers among convolutional with pooling (Conv/Pool) layers, after that, unacceptable CNN structure, the Conv/Pool as well as FC layers of every particle is treated separately.

E. Velocity determination

Some particle (P) provided the velocity is dependent on variance in terms of the global best (gBest), as well as particle best (pBest). So, it is required to calculate two variations: (gBest − P) and (pBest − P). This processes are complete in function Update Velocity(). For instance of such calculation, the two initial rows signify the variations (gBest − P) as well as (pBest − P), by variation from Conv/Pool as well as FC layers exposed individually. At last velocity is calculated with illustration of a number r regularly at arbitrary from [0, 1], and with selecting the layer from one of the 2 variations dependent on decision factor Cg. If $r \leq Cg$, the technique would choose the layer from the variation (gBest − P). If not, the technique will choose the layer from the variation (pBest − P). So, the decision factor Cg will manage how quick the informed particle structure is the gBest structure. Likewise the variation calculation, the velocity calculations are complete with individuating Conv/Pool layers from FC layers.

F. Particle update

Informing the structure of particle is mostly clear-cut process in the presented IPSOCNN technique. The informed particle structure happens in Update Particle() function. Another time, Conv/Pool layers are measured independent of FC layers. These techniques pursue the provided particle's velocity exploring to layers that must be changed. Layers are furthered or extracted from the particle structure based on velocity. But, the technique requires keeping way of number of pooling layers in structure. Instance of the velocity calculation takes place if the particles have the similar layer types as gBest and pBest. The inputs, simply a restricted number of pooling layers are permitted. When, behind inform, the particle finish up through further pooling layers than that permitted, pooling layers excessive are avoided from the particle's structure from final to initial layer in isolation.

III. PERFORMANCE VALIDATION

A. Dataset used

The computation of proposed technique has been sampled in contrast with Citrus fruit Diseases Image Gallery dataset as well as sample test images are depicted in Fig. 2 [14]. It is composed with 1000 images of different citrus fruits diseases like "anthracnose, canker, scab, melanose, leprosisetc". Here, test images consist of fruits and leaves including the dimensions of 100×150 pixels with 96dbi.

This work applies 6 citrus disease images that has "anthracnose, scab, black spot, melanose, greening, canker and so on". Hence, the chosen disease undergoes validation with the help of robust images and classified into respective classes. Therefore, the above data is given in Table 1 as well as the types are described as follows. Fig. 2 shows some sample test images. This part should contain sufficient detail so that all procedures can be repeated. It can be divided into subsections if several methods are described.

Table 1: Dataset Description.

Citrus Type	Total Images	Training Images	Testing Images
Anthracnose	100	50	50
Black Spot	80	40	40
Canker	120	60	60
Scab	100	50	50
Greening	100	50	50
Melanose	70	35	35
Healthy	100	50	50

Fig. 2. Sample Test Images.

B. Results analysis

Fig. 3 visualizes the results offered by the presented IPSO-CNN model. Fig. 3(a) shows the actual test image as well as image segmentation is revealed in Fig. 3(b). Finally, the defect region is effectively detected by the IPSO-CNN model and is depicted in Fig. 3(c).

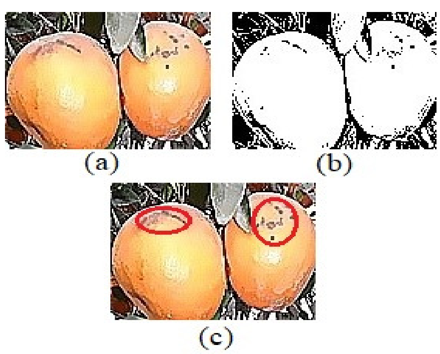

Fig. 3. Disease Identification on Citrus Fruit.

Table 2: Classification Accuracy and AUC of Proposed Method with Existing Methods.

Classifiers	Accuracy	AUC
IPSO-CNN	96.08	0.98
M-SVM	95.80	0.98
W-KNN	93.80	0.97
EBT	94.50	0.98
DT	94.50	0.98
LDA	93.50	0.97

Table 2 comprised the values obtained by presented IPSO-CNN and related techniques in terms of accuracy and AUC. Fig. 4 demonstrates a comparison of the accuracy values attained by distinct models. By considering accuracy, the Linear Discernment Analysis (LDA) method attained the least accuracy value of 93.50% denotes its inefficient performance. Followed by, W-KNN provides a slightly better accuracy value of 93.80%.

Then, Enhanced Bat Algorithm (EBT) and Decision Tree (DT) exhibits same outcome with the accuracy value of 94.50% that shows a gradual improvement than other models. Subsequently, Modified Support Vector Machine (M-SVM) generates a better value of 95.80% accuracy that depicts the additional enhancement. Finally, IPSO-CNN offers an optimal value of 96.08% accuracy. The above values proved that the presented IPSO-CNN model is the most efficient model when compared with other techniques.

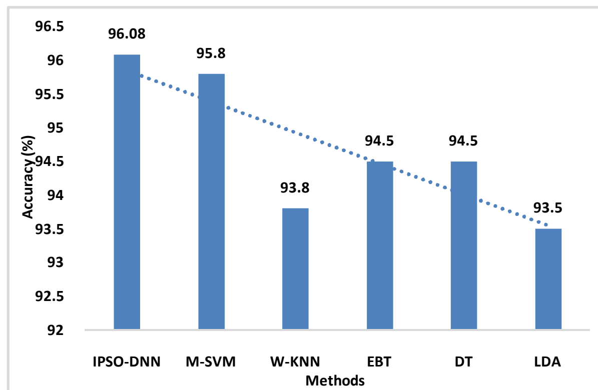

Fig. 4. Accuracy analysis of distinct models.

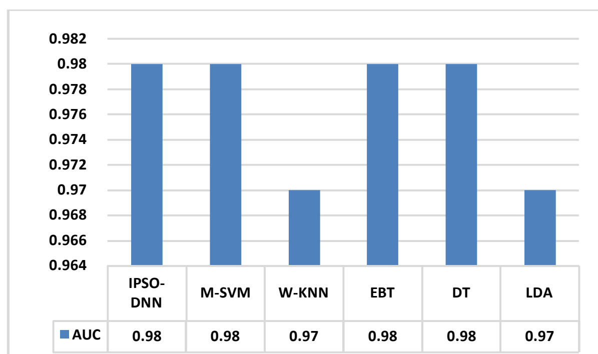

Fig. 5. AUC analysis of distinct models.

Fig. 5 displays a related accuracy values achieved by using standard frameworks. In case of AUC, the LDA approach attains a lower AUC of 0.97% indicates the poor computation. Secondly, W-KNN offers a little better AUC value as similar as LDA of 0.97%. Alternatively, EBT and DT show similar results with AUC of 0.98% which signifies the slower enhancement than alternate methodologies. Followed by, M-SVM provides a maximum value of 0.98% AUC that illustrates the better performance. At last, IPSO-CNN generates a best value of 0.98% AUC. Hence, the above metric shows that the deployed IPSO-CNN method is the most effective than alternate frameworks.

IV. CONCLUSION

This paper has developed an IoT based Smart Farming model and is presented by the use of IPSO-CNN technique for citrus fruit disease identification. The citrus fruits images are initially captured from the farming land by the use of camera sensors which captures the leaves and fruits of citrus. Then, it is connected to an IoT device named Rasbperry Pi3 which receives the image and transmits it to the cloud Thingspeak platform. Then, the training and testing of images takes place by the use of IPSO-CNN model. For experimentation, a benchmark citrus image dataset named Citrus Image Gallery dataset is employed. The simulation outcome indicated that the IPSO-CNN generates a best value of 0.98% AUC with the maximum accuracy of 96.08%.

V. FUTURE SCOPE

In the future, the presented model can be implemented in a real-time environment to assist farmers for early detection of disease.

Conflict of Interest: The authors don't have any conflicts of interest.

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