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A blockchain and deep neural networks-based secure framework for enhanced crop protection

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ABSTRACT

The problem faced by one farmer can also be the problem of some other farmer in other regions. Providing information to farmers and connecting them has always been a challenge. Crowdsourcing and community building are considered as useful solutions to these challenges. However, privacy concerns and inactivity of users can make these models inefficient. To tackle these challenges, we present a cost-efficient and blockchain-based secure framework for building a community of farmers and crowdsourcing the data generated by them to help the farmers' community. Apart from ensuring privacy and security of data, a revenue model is also incorporated to provide incentives to farmers. These incentives would act as a motivating factor for the farmers to willingly participate in the process. Through integration of a deep neural network-based model to our proposed framework, prediction of any abnormalities present within the crops and their predicted possible solutions would be much more coherent. The simulation results demonstrate that the prediction of plant pathology model is highly accurate.

1. Introduction

Across the world, the majority of crops are grown in monoculture. Such crops are more prone to pests and harmful insects than other forms of cultivation. Pests are organisms that damage or inhibit the growth of crops. These harmful organisms reduce plant density thereby adversely affecting yield. They also lower the quality of agricultural products [1]. To control these harmful pests and insects, we utilize physical, chemical, or biological methodologies. On the macroscopic scale, chemical methods have been in use more often across various parts of the world.

On a broad scale, crop protection must be done in both pre-harvest and post-harvest phases. Pre-harvest crop protection majorly involves protection against the growth of weeds and other non-useful herbs, harmful insects, insects that act as vectors for carrying disease, and locusts [2]. Post-harvest crop protection involves proper processing, storing, and transportation of crops [3]. We must do these at the earliest as the rate of increase of pests tends to increase exponentially and it may destroy the entire crop collection. The crops, in general, have to compete with 30 000 species of weeds, 3000 species of worms and other insects. There are also several other threats to the storage of crops which are caused by bugs and rodents.

Crop protection also implies using pesticides in the right proportion. Overdose shall result in affecting the soil quality which in turn affects crop production in the long run. Over usage of pesticides result in deaths of earthworms which also affects crop productivity. It is important to note that crop protection techniques also provide secondary benefits. For instance, usage of pesticides shall prevent tilling which helps in reducing the chances of land sliding to a great extent [4].

Crop protection is important to satisfy high public demand. It is innate and necessary. Recent stats indicate that pests reduce around 42 percent of the crop yield in the world and 28 percent in Europe [1]. Without pesticides, more than half of our crops would be lost to pests and diseases [5]. With the rapidly increasing population, the green revolution has helped to cope up with the rising agricultural demands of various communities to a large extent. One of the significant features of the green revolution involves the usage of pesticides and chemical fertilizers. Fertilizers and Pesticides have improved the quantity and quality of crops. Crop production has more than tripled since 1960.

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Moreover, crops like rice which is also a major crop has doubled in production. Similarly, wheat production increased by nearly 1.6 times. But still, there is a huge need for an increase in crop production. In the world, around 925 million people are facing deficit of food. According to a study conducted in 2013 by the Department of chemicals and petrochemicals, in India around 20–30 percent of crops are lost due to pests and insects annually, which amounts to nearly a loss of Rs. 45 000 crores [6].

Although, pesticides have helped in protecting crops, but pests exhibit mutations and increase their resistance against pesticides. This can be seen widely across developing nations. Many varieties of pests have significantly developed resistance and losses due to pest infections have increased with increase in productivity.

Climatic Conditions also affect crop productivity to a great extent. They cause unexpected losses among the farmers. Since pests activity on crops is highly variable to change in temperature, farmers are highly concerned about their crop fields. Due to attacks from certain insects like locust and some harmful pests, the farmers are often baffled to use the right protection technique [7]. Farmers require toxic chemicals to prevent crops from getting damaged. For instance, the recent locust attack in India which originated from Africa required organophosphates like Malathion 96 and Chlorpyrifos and other chemical pesticides. Except for Malathion 96, the other chemicals are highly poisonous. They were sprayed to prevent crop loss but eventually, they damaged the soil by making it highly toxic which is a great concern to farmers in India. Such attacks could have been prevented by using other crop protection techniques.

Integrated Pest Management(IPM) techniques are employed to reduce the growth and development of pests thus enhancing crop productivity. It is always done sustainably. It is not followed as a principle and instead acts as a philosophy to choose the right methodologies in the right situations to control pests' activity. The pests management strategies include cultural control, biological control, microbial control, behavioral control, physical/mechanical control, and then finally the most important method of increasing host plant resistance [8]. Usually, these methods are combined suitably to prevent pests attacks, therefore ensuring a sustainable environment.

Agronomic practices like crop rotation and intercropping of tolerant crops had resulted in diverting pests attack to the host crop. Methods like bagging have helped fruits to safeguard from pests and other physical damage. Although all fruits cannot be grown inside bags as they need air to breathe. Plowing has helped in destroying the soil residue while also destroying the growth stage of vegetable pests. Regular cleaning and sanitation practices have helped in controlling pests from spreading across the land. Technologies like micro-sprinklers create a less suitable environment for pests, therefore, reducing pests attack. Also practices of choosing the right seeds and changing planting dates have resulted in the reduction of pests attacks.

Apart from the cultural practices of IPM discussed above, Biological control has also significantly reduced the pest population. Introducing natural enemies of invasive pests has helped in successfully reducing their count in the field. For instance, Irradiated and sterile insects are used commonly against many invasive pests. Behavioral control is also a widely used strategy where baits, traps are used to disrupt the pest invasion. Baits are poisonous materials that attract pests with colors and odors. Some materials like Pheromone lures reduce pests mating potential, therefore, reducing the growth rate.

IPM techniques require frequent intervention in maintenance which is bound to error. To improve precision, sensors are deployed that capture information about plants and their environment [9]. In [9], libelium (an IoT platform) is used. It senses moisture content on leaves, the humidity of air, temperature, and solar radiation. Although, these measurements help in bringing about the enhanced crop productivity, the sensors do not capture pests activity. Additional sensors like the RGB camera can help in capturing Pests invasion and its related activity.

Data from crop and soil monitoring sensors is structured and enriched with timestamps and demography as mentioned in [10]. Blockchains are used so that the sensors' data can be prevented from being altered. After data preprocessing, machine learning algorithms are used to predict crop yield, the extent of pests attack, rate of crop growth, and also crop production enhancement recommendations.

Deep learning can be applied to detect pests and insects in the RGB images captured by sensor-camera. Object detectors like SSD, Mak R-CNN, Faster R-CNN help in classifying those images [11]. Ideally, highly accurate and low latency detectors are required to process the captured images to work in non-laboratory environments. Among many object detector models described in [11], SSD (single shot multibox detector) gives the best performer even for low-resolution images. This deep learning technique proves to be better than shallow machine learning algorithms. With this information, farmers are given the option of choosing the right methodologies to enhance crop productivity. Farmland anomaly detection can also involve large scale application of deep learning as described in [12]. These novel technologies reduce human intervention and therefore reduce error to a great extent in crop production. Blockchain and Deep Learning has found various application in several domains such as 5G [13], Edge computing [14], energy management [15], supply chain [16] and stock market [17]. Blockchain is also more extensively used in managing agricultural finances and also food supply chain [18]. Smart contracts are established between farmers and stakeholders who buy agricultural products. All the transactions are listed and block chained which guarantees a safe and suborn free method of handling money. This is especially useful for farmers facing economic problems. It is the inherent nature of blockchain, which is instrumental in bringing in security to the network [19–21]. Moreover, blockchain also helps in managing the food supply chain, making all the services transparent. This helps customers to buy safe agricultural products.

In this paper, we present a blockchain based framework for crowdsourcing the data generated by the farmer community to help them in crop management as well as provide incentives to them. Our research work incorporates a revenue model for incentivization along with ensuring privacy and data security by utilizing inherent property of blockchain. However, The transactions on the network may become time consuming and incoherent to large number of transactions due to ineradicable nature of blockchain. In order to accommodate coherent and precise predictions, we use deep neural networks for anomaly predictions within the crops.

2. Related work

In recent times, research on Deep Learning along with blockchain to make crowdsourced applications and frameworks has seen an explosive growth. Khan et al. [22] proposed a blockchain-based, resource-efficient solution for private and secure IoT. Gargi et al. [23] designed a novel privacy anonymous IoT model. They presented an RFID proof-of-concept for this model. Their model leverages blockchain's decentralization for on-chain data logging and retrieval. Their model solution will allow moving objects to send or receive notifications when they are close to a flagged, probable, or confirmed diseased case. Ali et al. [24] proposed a Long Short-Term Memory (LSTM) based on time series for the prediction of the maximum, minimum, and mean values of the air temperature, relative humidity, pressure, wind, and dew point. Microclimate data inside and Macroclimate data outside the greenhouse are collected and used for the best-fitting LSTM model analysis. Ali et al. [25] present a model for predicting environmental atmosphere for producing tomatoes in greenhouse. Ali et al. [26] proposed a Wireless Visual Sensor Network (WVSN), machine learning and image processing based solution to observe any deficiency, pest, or disease presenting on the leaves of the plants. They distribute camera sensors throughout the greenhouse. Each sensor node captures an image from inside the greenhouse and uses machine learning and

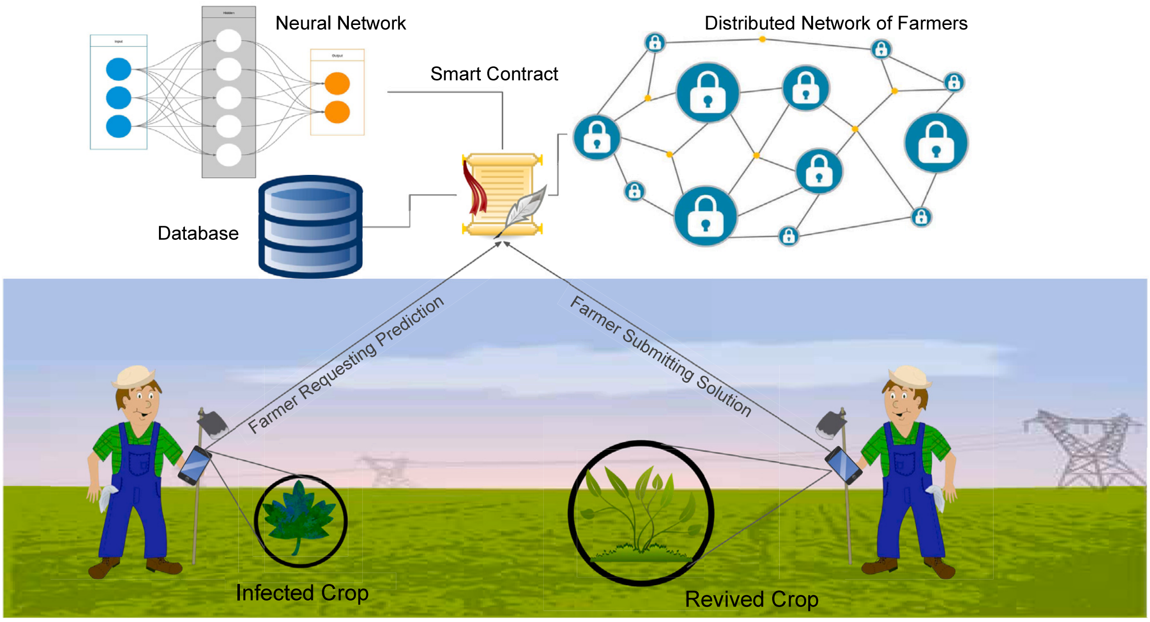

Fig. 1. Overview of the complete model.

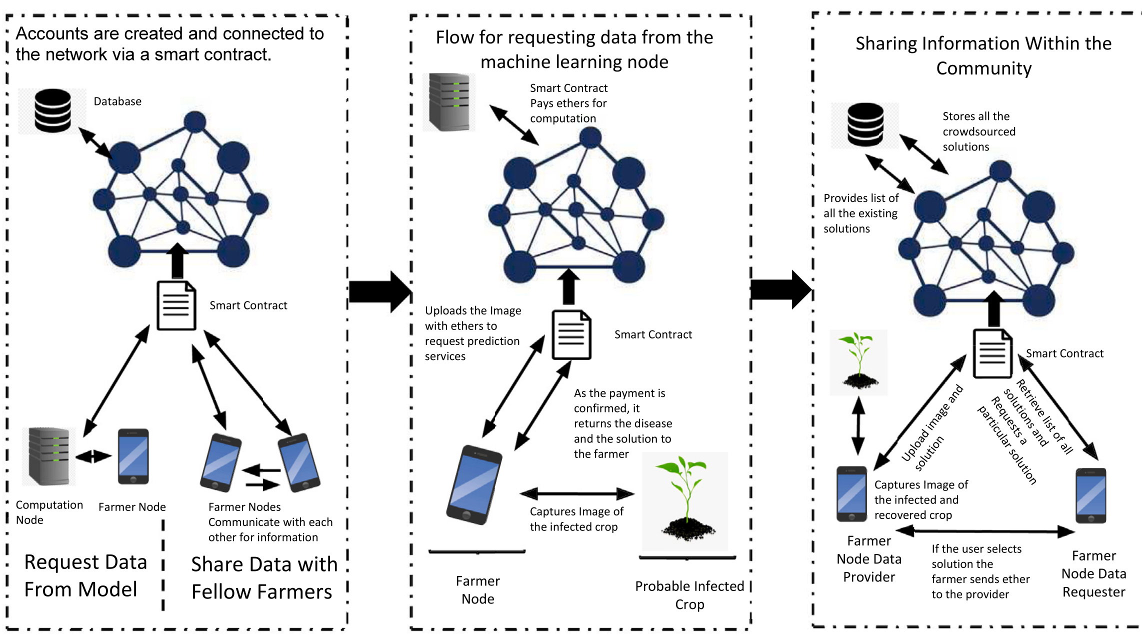

Fig. 2. Functions performed by the model in depth.

image processing to detect fungus. In the field of agriculture and farmer communities, much research has contributed to their works. Zhang et al. [27] proposed the solution using image processing methods and machine learning techniques that enabled them to count the total number of grain bearing tips of wheat plant. Though this approach showed promising results and handles the problem of occlusion due to different angles of inclination of the two ears, still this method lacks the performance under the complex field conditions.

While blockchain-based crowdsourcing has not been implemented much in the domain of protection of crops from diseases, many different applications have been developed for the benefits of the farmers. These applications do not incentivize the farmers to become part of a peer to peer network. Mingjie et al. [28] proposed a promising method for image enhancement based on two different algorithms for high and low frequencies after performing a wavelet transform. A DMS-Robust Alexnet architecture is proposed for maize disease classification, which is an improvement of the traditional Alexnet architecture. The model is tested to classify a test image into either of the 6 maize leaf diseases or as healthy.

Various researchers have employed the methods of deep learning algorithms like CNN [29], Faster-RCNN [32], RCNN [33] or ResNets [34], etc. Wei-Jian Hu et al. [30] proposed the solution for crop diseases using the MDFC-ResNet algorithm. The authors used the IoT systems to their advantage automating the process of feeding the data into the deep learning model. They showed promising results with an accuracy of 82.24% but could not use different color space in preprocessing for better target detection.

Table 1
Comparison with related work.

Reference	Contribution	Strengths	Weakness
Dongyan Zhang et al. [27]	Image processing and ML-based methods for detecting wheat ears	Outperformed the previous model in different varieties	Tested in laboratory conditions
Jie Xu et al. [29]	CNN to classify Zanthoxylum armatum into healthy or rust.	Introduced Neural Networks for plant disease detection	Targets only one crop species
Wei-Jian Hu et al. [30]	Used MDFC-ResNet and IoT for accurate detection of crop diseases	Automation of detection using IoT and messaging to farmers	No communications between farmers or incentives to farmers
Our proposed approach	Introduction of blockchain-based crowd sourcing platform for detection of crop diseases and setting up peer to peer communication between farmers providing them incentives and a platform for sharing their solutions	Provides a secure and cost-efficient way to detect crop diseases. Our platform also allows them to earn incentives [31] by contributing towards helping the fellow farmers increasing the reach of our diseases.	The transaction on the network may take some time to complete and does not support frequent large transactions owing to the inherent behavior of blockchain.

Although, there have been various attempts to predict plant and crop diseases [35–37], most of them make use of mathematical models using Image processing on laboratory collected data. Various diseases and problems related to plants and crops have not yet been identified by such systems but solutions are found by many people. In such situations, the best way to share the solution and help the masses facing similar issues is to get the solutions directly from the farmers who implemented them. This calls for a secure, efficient, and cost-effective crowdsourcing model for the detection of plant diseases. Following are some highlights of our model that addresses these points:

- Using blockchain to solve the security related issues and constraints.
- Ensuring high participation of farmers using a novel incentive-based approach.
- Provide an efficient model that can identify and propose solutions to various crop diseases.

A detailed view of how the system works and an explanation of all the steps involved in our crowdsourcing approach has been presented in the following sections. Table 1 compares the recent related works in direction of crop protection in terms of their contributions, strengths, and weaknesses.

3. System-model

Fig. 1 gives the overview of the proposed model and methodologies to interact with the fellow users. All the farmers and the Machine Learning nodes belong to the same network and can constantly interact with each other, having the flexibility to enter and exit the network at any point in time. There are some sets of nodes with high computation power and resources. These nodes act as the Machine Learning nodes and can process requests at a higher rate. Salient features of the proposed framework are:

(1) Farmer's account is created as soon as he wishes to participate in the network. Every account has its own unique identity in terms of a set which includes an address, a private key, and a public key. Each transaction on the network is verified by the digital signatures made by the senders private key. This keeps all the adversaries from manipulating the information.
(2) Our framework provides two options to the farmers. First option is that the farmers can ask the powerful machine learning nodes about the issues with crop/plant by uploading an image. In the second option, the farmer could contribute to the crowd-sourced solutions by providing images before and after the intervention.
(3) The network stores the information about the images and the solutions proposed by the fellow farmers in a database which in turn increases our reach to newer diseases and allows retraining of our model for more diseases.

Table 2
Classes on which model is trained.

Classes	Bell pepper bacterial spot Bell pepper healthy Potato early blight Potato late blight Potato healthy Tomato bacterial spot Tomato early blight Tomato late blight Tomato leaf mold Tomato septoria leaf spot Tomato spider mites two spotter spider might Tomato target spot Tomato yellow leaf curl virus Tomato mosiac virus Tomato healthy

(4) For getting help from the machine learning model the farmer needs to upload the image to the network. For using the services of the model the farmer first needs to pay a fixed amount to the smart contract. After payment is made, the model returns the disease detected and the proposed solution for that disease.
(5) Farmers can also find a solution by connecting with his fellow farmers on the network. All the solutions proposed by the farmers are available to everyone on the network. The farmer can choose which solution can be a viable option for his problem statement through their analysis according to the constraints faced by them. He can then pay a fixed amount to the fellow farmer for getting the solution.
(6) All the images uploaded by the farmers are stored in a database which can be accessed for furthering the reach on diseases and training the machine learning model.

Fig. 2 shows the detailed technical steps being followed in the process of enhanced crop protection. The model is based on Ethereum network and uses Proof of Work(PoW) as the consensus algorithm. The farmers pay the required amount as the proof before getting the solution from the network about the disease.

4. Proposed network model

Consider a set of farmers $A = \{A_1, A_2, A_3, \dots, A_n\}$ where n denotes the number of farmers in our network at a given point of time. Any farmer $A_i \in A$ can either request detection of their problem using the machine learning node for some tokens or can contribute to the network with their solution for a particular problem. Any farmer in exchange for tokens can also adopt a solution prescribed by any other farmer. In our framework, Convolutional Neural Networks (CNN) [38] is used to classify the images into different classes listed in Table 2.

4.1. Preparing data for training the model

To get the optimal results all the images had to be identical. The images where of different resolutions and classes. The images had to be re-scaled and color toned to get an identical-looking dataset. All the images were resized to 256 × 256. Hence our solution functions well in case of use different Image Sizes also as each input image is scaled to 256 × 256 size and is further passed on to the deep neural network model for appropriate classification. This makes our proposed solution robust to input image size differences. Image augmentation is then used to generate additional data using rotation, scaling, shifting, and zooming. As shown in Algorithm 1.

Algorithm 1 Data Preprocessing

```
procedure CONVERT-IMAGE(image)
    image ← RESIZEIMAGE(image)               ▷ Size:256x256
    image ← BRIGHTENIMAGE(image)
    imageArray ← CONVERTTOARRAY(image)
    imageArray ← SCALEARRAY                  ▷ Divide value by 255
    return imageArray
end procedure
```

4.2. Convolution Neural Networks (CNNs)

To extract features of images, and to classify them into different classes, a CNN is used. Steps involved are:

4.2.1. Pass the input image to convolutional neural network

Consider an image, this image can be represented as a set of pixels. We use a filter to analyze the influence of nearby pixels to the image. Filters are capable of keeping track of spatial information and adapt to extraction of features like edges, curves or lines. Detecting the edges of the leaves in the image allows us to remove the unwanted clutter from the image and helps us better localize the leaf and abnormalities in it. The image passed will be processed through different layers of the model and undergo convolution, pooling and normalization operations sequentially. Table 4 presents a complete layerwise breakdown of our CNN model.

4.2.2. Convolute the image

Convolutional Layer is responsible to extract the features by passing the image through high pass filters where pixel change occur very quickly with high intensity. Now to explain how features are extracted, we consider a filter (kernel) and pass this kernel over different sectors of our image and obtain a matrix which is called the feature map of the image. This feature map (G) is calculated based on the following formula,

$$G[m,n] = (f * h)[m,n] = \sum_j \sum_k h[j,k] f[m-j, n-k] \tag{1}$$

where G defines the feature map matrix, f defines the input image, h defines the kernel matrix, m *and* n defines the indexes of the kernel matrix. The size of image after passing it through a layer of filter is given by:

$$Size(G) = (Size(f) - Size(h) + 2 \times Padding) \times Stride + 1 \tag{2}$$

where Size(M) operator refers to the value of n for a nxn matrix M and padding is the extra layer added such that the input image dimensions evens out with the dimensions of the kernel matrix. Stride is defined as how many pixels does the kernel matrix is shifted after each computation.

Table 3
Defining the variables in Eq. (4).

$\vec{z}$	The input vector of the function $(z_0, \dots z_K)$
z_i	All the z_i values are the elements of the input vector to the softmax function
e^{z_i}	The standard exponential function is applied to each element of the input vector.
$\sum_{j=1}^{K} e^{z_j}$	The term on the bottom of the formula is the normalization term. It ensures that all the output values of the function will sum to 1 and each be in the range (0, 1).
K	The number of classes in the multi-class classifier.

4.2.3. Apply pooling and ReLU activation function

The next step is to reduce the size of the image for better localization of the feature to be extracted. This is obtained by using the pooling methods. Pooling is done to achieve a smaller image which in turn decreases the complexity and the computations required. We have used the method of Max Pooling. Max Pooling finds the maximum value from the feature maps and creates a new map.

The activation function of a node defines the output of that node given an input or set of inputs. We are using the ReLU activation function. It stands for the Rectified Linear Unit for non-linear operation. It solves the purpose of adding non-linearity to the network because in usual cases, the real-world is highly non-linear.

$$ReLU(x) = \begin{cases} x & if \quad x \geq 0, \\ 0 & if \quad x < 0 \end{cases} \tag{3}$$

4.2.4. Flatten the output and feedforward it to fully connected layers

For the obtained feature maps with weights, 3D matrices need to be converted into single values to predict the classes. We use the softmax function which is responsible for mapping the values to a range of 0 to 1 so that they can be interpreted as probabilities. The softmax activation function is a generalization of the logistic regression and is rightly called multi-class logistic regression making it a suitable choice for multi-class identification. The softmax activation function is only used when the output classes are mutually exclusive. The formula for softmax is described below in Table 3,

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{4}$$

4.3. Training a neural network

For supervised learning models, there is an essential step of training the model. For a convolutional neural network, all the examples in our training dataset include an RGB image and an output label y_i. For our model, the output label y_i can take 15 values described in Table 2.

As the data preprocessing is done and images are converted into numerical arrays. It is split into test and train dataset, where the test dataset was 80% of the total dataset, and the remaining 20% was the training dataset. The test dataset was divided into smaller batches of size S and thus total batches Q

$$Q = \frac{Total\ Number\ of\ Train\ Examples}{S} \tag{5}$$

These batches where passed through the following CNN model to extract the features, to which we added the Adam optimizer [39] for enhancing the learning rate and increase accuracy.

When the image is passed the CNN model it passes through several layers. The learning parameters calculated using Eq. (1) for every layer is defined as follows:

- **Input Layer** only reads the image and provides the shape of the image. This layer has nothing to learn and thus total parameters learned are 0. Input layer passes the image to the CONV Layer.

- **Convolutional Layer** This layer is responsible for all the learning. The weight matrices are calculated in this layer. If the number of the filters is 'k' with size of $m \times n$ d being the number of filters in the previous layer then the total number of parameters calculated is given by the following equation:

$$parameters = (m \times n \times k + 1) \times d \tag{6}$$

- **Pooling Layer** This layer is responsible for reducing the size of the image using the values of the parameters calculated. We used MaxPooling, which takes the maximum value of the calculated parameter in Eq. (1).
- **Fully Connected or Output Layer** This layer has the maximum amount of parameters to learn since every neuron is connected to every other neuron of the previous layer. The number of parameters to be calculated having c neurons in current layer and p neurons in previous layer is giver by:

$$(c \times p) + 1 \times c \tag{7}$$

Algorithm 2 Disease Detection Based on Blockchain and Deep Neural Network

Input: Request from a farmer on network along with an image of infected crop.
Output Final detection of the disease along with the solution.

1: Obtain the image from the farmer willing to use the service of the prediction node.
2: From the base64 image obtained from the user create the image.
3: Pass the image into the data preprocessing algorithm 1
4: Feed the image obtained to the CNN network for the probabilities
5: Match the probability with the appropriate class
6: Find the solution for the particular class and send the information back to the farmer.

4.4. Optimizing training

For optimization of training of the neural network model and updation of the learning factor of each network weight, we utilize Adam Optimizer.The authors describe Adam as combining the advantages of two other extensions of stochastic gradient descent, The Adaptive Gradient Algorithm(AdaGrad) and the Root Mean Squared Propagation Algorithm (RMSProp) [40]. Both of these algorithms maintain a per-parameter learning rate that is responsible for improving performance. Adam realizes the benefits of both AdaGrad and RMSProp.

The updation rule for Adam optimizer:

$$\Theta_{t+1} = \Theta_t - \frac{\alpha \cdot \widehat{m_t}}{\sqrt{\widehat{v}_t} + \epsilon} \tag{8}$$

where,

$$\widehat{m_t} = \frac{m_t}{1 - \beta_1^t} \tag{9}$$

$$\widehat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{10}$$

$$m_t = \left(1 - \beta_1\right) g_t + \beta_1 m_{t-1} \tag{11}$$

$$v_t = \left(1 - \beta_2\right) g_t^2 + \beta_2 v_{t-1} \tag{12}$$

where,

- ϵ is a small term preventing division by zero usually 10^{-8}

Table 4
Layer breakdown of the CNN model.

Layer	Output shape	Features
Conv2D	256 × 256	32
ReLU activation	N/A	N/A
Normalization layer	N/A	N/A
MaxPooling	85 × 85	32
Dropout layer	N/A	Factor = 0.25
Conv2D	85 × 85	64
ReLU activation	N/A	N/A
Normalization layer	N/A	N/A
Conv2D	85 × 85	64
ReLU activation	N/A	N/A
Normalization layer	N/A	N/A
MaxPooling	42 × 42	64
Dropout layer	N/A	Factor = 0.25
Conv2D	42 × 42	128
ReLU activation	N/A	N/A
Normalization layer	N/A	N/A
Conv2D	42 × 42	128
ReLU activation	N/A	N/A
Normalization layer	N/A	N/A
MaxPooling	21 × 21	128
Dropout layer	N/A	Factor = 0.25
Flatten	N/A	N/A
Softmax activation	Fully connected layer	

- α is the learning rate equal to 0.001
- g is the gradient
- β_1 and β_2 are the two moments or the decay terms which Adam requires us to maintain

Algorithm 2 defines the steps followed by the framework.

5. Numerical analysis and results

5.1. Image recognition settings

The Convolutional Neural Network was implemented using the Keras framework. The model consisted of 28 layers with a total of 58,102,671 parameters out of which 58,099,791 were trainable. All the images were augmented for better recognition with the use of rotation, height, and width shift with zoom and horizontal flips. The softmax activation function was used to define the output. For increasing the accuracy and avoiding overfitting of the Deep Neural Network four dropout layers were used with the value of 0.25 after layer 3, 0.25 after layer 13, 0.25 after layer 21, and 0.5 after layer 26. For training the network the optimal batch size came 32, epochs came out to be 50 and the steps per epochs came out to be 73. Adam optimizer from the Keras framework with a learning rate of 0.001 and decay of 0.00002 was used for faster convergence.

5.2. Performance evaluation of the framework

Our model directly targets factors including time, incentives and solutions for crop protection, which in turn motivates all the farmers to be more active on the network and increase their contributions. In the search for more incentives and better solutions, this would also strengthen the network which in turn increases the accuracy and authenticity of the network. Fig. 3 shows some prediction results obtained for leaf disease identification within our framework, which would help farmers in ensuring adoption of correct crop protection measures as per the problem faced.

Existing architectures do not include incentives nor they connect farmers to each other. Adding the missing incentive model, the same farmer increases the contributions and now using the predictions provides better solutions.

Figs. 4–7 evaluate the different optimizing approaches used in the training of the model. The major optimizers compared were RMSProp

Fig. 3. Result images for leaf disease identification.

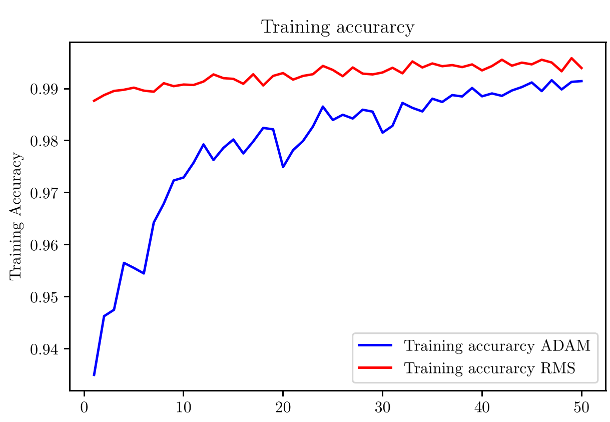

Fig. 4. Training Accuracy Adam vs. RMSprop.

Fig. 5. Training Loss vs. RMSprop.

and Adam optimizer. Though with the RMSProp the convergence was faster with low losses and higher training accuracy, the validation accuracy was not up to the mark as compared to the Adam optimizer. The validation loss was also on a higher side as compared to the Adam optimizer, thus making the Adam optimizer a clear favorite.

Fig. 8 evaluates how our model monetarily benefits the farmer on a monetary basis. The average cost of identifications and research for the treatment of plant diseases is shown in the figure by the red line. This cost is constant as it is an expense that the farmer incurs in identifying different features or diseases in their crops. This cost is a burden to many of the farmers, but our model can help cope up with this extra cost. If the farmer regularly contributes to our model by providing solutions to different diseases, then over time the incentives provided by the proposed framework overcomes the average cost.

6. Future directions

One of the most important methods in controlling pests is to improve the resistance of host crops against pests. Genetic modification of crops can be an effective measure for developing resistance against crops. Although this methodology turned out effective against a wide variety of insects, for a minority amount of species such methods of development of genetic resistance may not be effective. To prevent this, farmers are generally advised to use other strategies along with

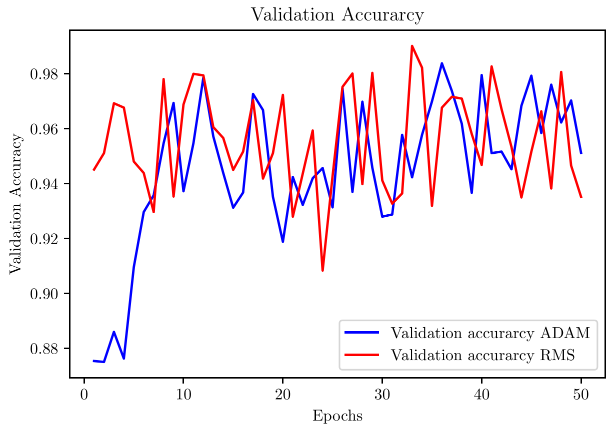

Fig. 6. Validation Accuracy Adam vs. RMSprop.

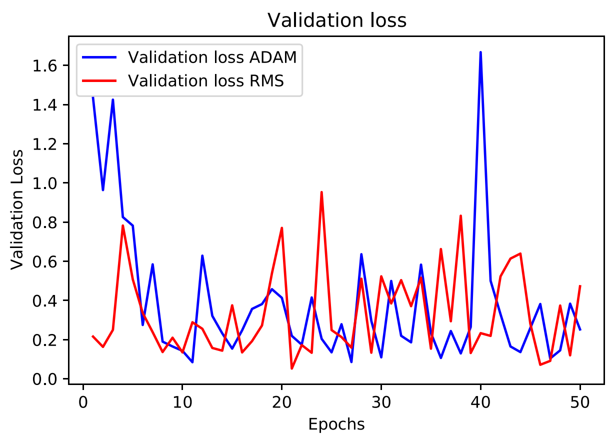

Fig. 7. Validation Loss Adam vs. RMSprop.

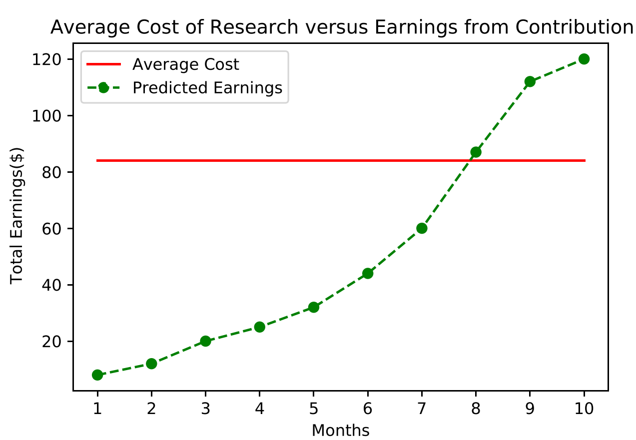

Fig. 8. Average cost & earnings in dollars (estimated) [41].

improving crop resistance to prevent on-field growth of resistance by pests. Judicious and well planned crop rotation can be an effective strategy to cease genetic resistance development among pests. Our present model can support multiple users, though the transaction time may be higher but combined with a parallel blockchain, this model can be scaled up horizontally. The present machine learning model is currently trained on 3 categories of plants with different diseases as subcategories. As the number of unfulfilled requests increase, the dataset grows and model can be retrained efficiently. We aim to extend our work in future to allow farmers get appropriate suggestions for crop management and crop rotation patterns using semantic segmentation of farmland UAV Images. The results would also help farmers identify the correct regions for cultivation and patterns to be adopted in order to reduce wastage of resources in cultivation and harvesting. Our As a future extension of this work, we plan to introduce a feature that detects intrusion on the farms and could contact the concerned farmer at the right time. Due to inherent behavior of blockchain, the proposed framework may not support large number of transactions and be slow. However, a parallel blockchain system can nullify these barriers to a good extent. Each subchain in parallel structure can dynamically shift the quantity of transactions as per the capacity. Dynamic sharding allows the underlying processing speed to not get affected by transaction volume. Hence, inclusion of parallel blockchain structure can be advantageous in nullifying the drawbacks of our proposed framework.

7. Conclusion

For solving two main problems of any crowd-sourced application viz., the motivation of the users, and the privacy concerns of the users connected to the service, in this paper, we proposed a framework for securing and increasing crop production using blockchain network and deep neural networks. Being the part of the network provides users a great opportunity to earn incentives and cryptocurrency by providing their solutions and helping fellow farmers. They can then earn these incentives as well as obtain a report on the problems faced within their farm by using the services of the machine learning nodes. For predicting the diseases and recognizing them we employed the Convolutional Neural Network algorithm. The results show that our model should be successful in reaching a higher number of participants due to incentivization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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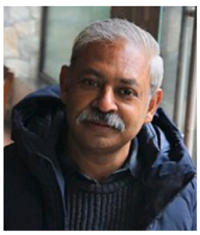

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