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IOT-based Monitoring System for Oyster Mushroom Farms in Sri Lanka

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ABSTRACT Oyster Mushrooms are a type of a fungus which is very sensitive to the environmental factors and vulnerable to diseases and pest attacks which directly effects local trade and export strength. Mushroom is a climacteric type of food which continues its cycle even after harvesting. The mushroom farming process still uses manual mode such as the identification of diseases uses a farmers eye visually, harvesting of mushrooms are decided based on the visual appearance while the environmental factors are decided based on gut feelings. These methods has its limitations which requires more potential to improve both the quality and capacity of mushroom production. With the advancements of technology, this farming process can be performed with the aid of an IoT device and deep learning model. This research applies Convolutional Neural Networks (CNN) with Mobile Net V2 model to detect mushroom harvest time and any disease spread with an accuracy of 92% and 99% respectively. Long Short-Term memory (LSTM) to analyze the detected environmental factors with an accuracy of 89% and this system predicts the yield of mushroom production with the support of LSTM model with an accuracy of 97%. This developed system which aids mushroom farming activities is connected with the farmers through s mobile application.

KEYWORDS: Harvest, Monitoring, Mushrooms.

I INTRODUCTION

Mushrooms are a type of edible fungi which expands to a wide range of varieties. Oyster mushrooms (Pleurotus Ostreatus) is one of the most dominant type of mushroom which is consumed within Sri Lanka. It is well known for its delicate texture. Mushrooms are being highly consumed among Sri Lankans for its national benefits [1] by which the local trade has failed to full fill the market demands.

Mushrooms are grown inside closed, thatched mud houses, in which maintaining the required environmental factors such as temperature, humidity, and Co2 is difficult with the weather changes [2]. The cultivators are still deciding when to harvest their mushroom products, by their gut feelings, which ends up in less life for their packed products. Mushrooms being a type of fungi, they are very vulnerable to diseases. When diseases spread at a high-rate, cultivators often fail to recognize the disease accurately and thereby fail to apply the correct remedy. Mushroom farmers also fail to obtain a better yield owing to the inefficiencies in the cultivation methods. These, methods require quick refinement for the farmers to obtain their profitable yields

II RELATED WORK

G.M Fuady, A.H Turoobi, M.N Majdi,, M. Syaiin conducted an empirical Study of Extreme Learning Machine, ELM to maintain the environmental factors of a mushroom farm house[3]. This research uses a Single Layered Feed Forward Neural Network (SLFN) with the moderation of H inverse matrix or ELM to create a model to maintain factors such as temperature and humidity within a mushroom farm. Together this research develops a hardware panel with a mist maker and exhaust fan to control and DHTII sensor to monitor humidity[3].

Palraj M.P, Hema C.R, R. Pranesh Krishnan and Siti Sofiah, Mohd Radzi presents a design to detect the ripeness level of a banana fruit[4]. This research manipulate a Neural Network model developed using the error back propagation. The specimen used for this research is a banana. Data for the dataset collected at difference ripeness levels of the banana from good condition to rotten level. This process is a combination of three steps Image Pre-processing phase followed by feature extraction phase and classification phase of bananas. First the image is captured using a digital camera at a resolution of 320×240 pixels. Then the captured image is recomputed to image's color index. The RGB color component is extracted and displayed using a grey scale image. The components of the colour of the recomputed image are rescaled using simple heuristic methods. A histogram for the recomputed image is achieved and then it is used as a feature vector to recognize the level of ripeness of the banana fruit. This work proves the accuracy of ripeness detection as 96% [4].

Andi Wahju Rahardjo Emanuel has used five steps for recognizing and classification of diseases which spread on plants using Image Processing[6]. The first step is Image Acquisition using a digital device. Image resizing, smoothing, increasing contrast and image enhancement is used in the second step Image Pre-processing. The third step is removing the noise and Image Segmentation. In the fourth step, Feature Extraction is based on colour, shape, edge, and texture. The final step of image processing is Classification. Convolution Neural Network (CNN) trains the input and classifies output responsibility and has the capability of detecting disease. At this step model's accuracy is also verified [6].

According to Md Al Maruf the easiest way to accomplish provide and demand optimization is to create algorithms that forecast potential demand based on historical demand data and the variables that influence demand[5]. The paper examines three different Machine Learning Algorithms to predict a mushroom farm's future demand for mushrooms based on data from the previous few months and thus to produce the best possible algorithm for predicting mushroom sales. The paper also evaluates the type of data in each of the three algorithms that produces the best possible result, thus differentiating the algorithms based on the type of data they can best work on.

'Mangosteen' has become a significant export and trade item in the country of Indonesia. It is believed that this fruit changes with time, therefore there is a possibility of fruit ripening during transport and storage. Thereby, there is need to detect the maturity level of mangosteen before releasing to market. This process is yet to be done by manual methods, which involves in human supervision which will have a limited capacity of identification. In this research, Oka Sudana, Putu Bayupati and Dewa Yudiana demonstrates a digital system which is capable of detecting the maturity level of the fruit [22].

A study by Manish Chhabra, Rohan Gaur and Parminder Singh introduces a technique to detect the ripeness level of the mango fruit [23]. A neural network methodology is used. for the classification of mangoes according to its ripeness levels. In this study, the mangoes are classified into two classes 'Ripe Mango' and 'Unripe Mango'. The mangoes ripeness was identified with an accuracy of 95.5% and 200 samples were considered.

There are various researches performed based on different types of fruits, but very few have assessed mushroom cultivation. However, methods used by other fruits tends to use much similar methodologies. The paper which presents temperature and humidity control of oyster mushroom based on microcontroller [3], monitors the farm house environment factors in spite of that our application has achieved to monitor the environmental conditions and also to provide control recommendations in a timely and customized format which balances the maintenance of all three factors. Determining the Ripeness of a Banana [4], research determines the maturity level however our application is able detect the maturity and provide a timely alert to harvest the mushroom which the mushroom will be plucked at the peak quality point. Plant leaf detection [5] detects the diseases but our application nevertheless has found out the most significant disease to the Sri Lankan context to give Sri Lankan farmers the best use.

III METHODOLOGY

This research aims to address issues that the mushroom cultivators face due to the manual farming practices followed by them. Thereby, a study was conducted aiming to develop smart mushroom farming solution to the mushroom cultivators in Sri Lanka to solve the issues that are left unaddressed.

A Data gathering for dataset training

At present, fundamental information required for mushroom farming in the Sri Lankan context is not readily available. Therefore, the research group initially carried out a survey among a group of mushroom farmers from different areas of the country and identified essential data such as the ideal environmental conditions required for farming in Sri Lanka, the frequent types of diseases which may develop with in mushrooms in Sri Lanka, criteria for harvesting mushrooms and specific yields from cultivations. Currently there is no standard database of images of unique mushroom diseases to Sri Lanka and images of mushrooms at different stages of their life cycle. Thereby the research team selected three private mushroom farms and collected a total of 748 images of five diseases on mushrooms and 1887 images of mushrooms at different stages of their life cycle.

B System Overview

The system consists of 04 functions: Environment Monitoring function, Harvest Time Detection function, Disease Detection and Recommendation function and the Harvest prediction function. The farmer, provides the required inputs to the respective functionalities to ease the farming methodology. The required outputs to the farmer is provided to him through a mobile application. The overview of the SMF functionality is illustrated in figure 1.

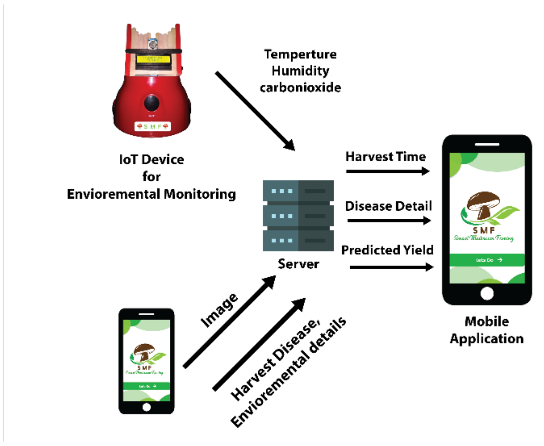


Figure 1: System Overview Diagram

This system is divided into four different segments in order for it to provide solutions to the technological spaces within the mushroom cultivations in Sri Lanka. Each segment of this system is elaborated below:

1 *Monitoring of Environmental Factors and recommendation for controlling*

Oyster mushrooms grow well within specific environmental states such as temperature, humidity, and carbon dioxide Co2 in air. They grow and develop in a temperature that range from 26 to 30 °C, humidity within a range of 80 to 90 percent and carbon dioxide level in a range 800 to 1500 ppm as illustrated in Table 2.

Table 1: Environmental factors Threshold Ranges

Environmenta Factor	Threshold Range
Temperature	26 – 30 °C
Humidity	80 – 90%
Carbon dioxide	800 – 1500 ppm

The data required to create the dataset was collected by planting the hardware, IOT device developed to monitor the mushroom farms environmental factors, in the three selected local mushroom farms. Then the monitored levels of three factors were recorded every hour for 24 hours. Finally, a dataset of 4000 record were generated to train the machine learning model. The monitoring unit is setup in the farm to monitor the basic environmental factors temperature, humidity and carbon dioxide of the oyster mushroom cultivation, initiates with the detection of sensor readings as inputs. The inputs data of time, temperature, humidity, and carbon dioxide are refined using a Node MCU as a microcontroller.

This circuit uses two methods to power it, the main power supply (230 v) and the auxiliary power supply. Here we need to consider two ways to finish and activate the final device according to our needs. That is, the main current (230 v) from the main supply has to be reduced to fit the circuit. (230v to 5V) and the recharging process of the auxiliary power supply. To accomplish this the main power supply is reduced to 5v using a converter circuit and then connected to the switch via an auxiliary power supply. The circuit, which is powered by these power supply processes, connects to two main sensors and detects and collects environmental factors. Namely the DHT11 sensor and the MQ-2 sensor. This DHT11 sensor is capable of detecting both ambient temperature and ambient humidity. The MQ-2 sensor will also be used to measure atmospheric gases. Therefore, CO2 gas is measured according to our requirement through this sensor. An LCD display is attached to the device to display the factor readings at the real time. The structured diagram you can see in Figure 2 is the circuit diagram of the IOT Environment Factors Monitoring Device.

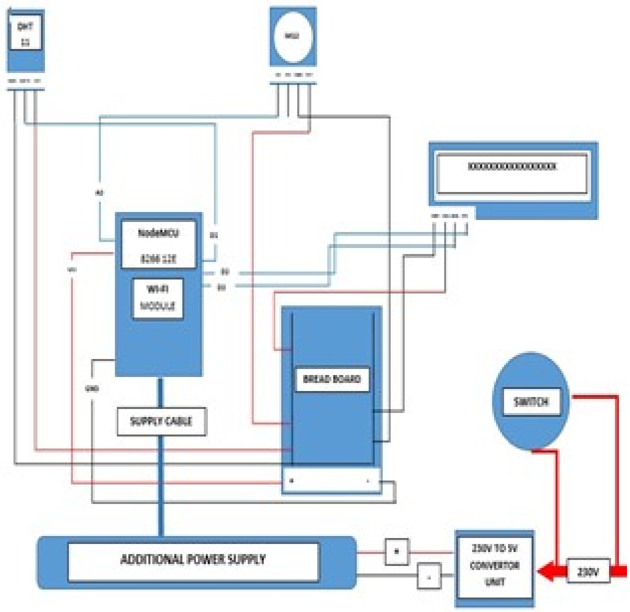


Figure 2 : Schematic Diagram of the IOT device circuit

Therefore, the device that is finally produced allows the farmer to take this device to any corner he wants in the house as per his need.

That's because this is a device that is designed to be packed together and carried in the hand which makes it fully portable as illustrated in Figure 3 (final deice image).

The environmental factors of the farm are monitored for 12 hours, every hour. Then by learning the pattern changes with respective to time by a trained model by Long short-term memory (LSTMs), the output in Figure

Figure 3: IOT Environment Factors monitoring Device

4 will be given as a timely recommendation for how long the control equipment's needs to operate to bring back the environmental factor back to normal which will cut down the resource wastages. This recommendation is customized as in the time recommended for a particular equipment will only effect the factor needed to be changed while keeping other two factors unaffected In the specialism of

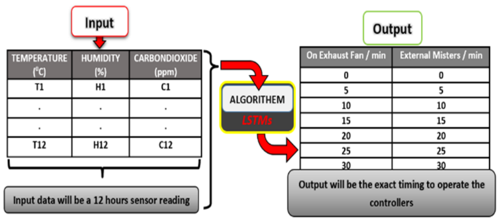


Figure 4 : Final LSTM output

deep learning, LSTM is an Artificial Recurrent Neural Network (RNN) [13]. LSTM networks are ideal algorithms in making predictions, classifying objects and processing based on time series data [14]. LSTM's were evolved to handle the dispersing gradient problems which can be experienced when training traditional RNN's. A usual LSTM contains a cell an input gate (x,1) and output gate and a forget gate.

The model created for this system to train the collected data was LSTMs was used. The user data is passed through an API into the LSTMs [15]. After data set was created, second step was to train the data set, select the future values in data set then it scale down to min, max. The scale down, transfer 1D array to column vector. A dataset of 5000 data records were created. Then this data is broken down to windows of 12 record (12 rows). This resulted in 417 data records. Then out of 417 records 90% was used for training and 10% was used for testing purposed. Then the model was tested.

Using this part of the project a farmer receives a customized recommendation, to bring the particular factor to its normal levels having the other two factors remain unchanged. If any of the environmental factors changed, the farmer will be notified immediately on his phone, and with that notification, the farmer is notified how and for how long to use his equipment to bring the mushroom farm back to its normal environmental conditions.

The timely recommendations are given respectively. If humidity increase more than the required levels the function generates the timely recommendation to on the exhaust fans in order to reduce humidity. If humidity decreases than the required levels the timely recommendation will be generated to turn on the external misters. If the temperature increase than the required levels the timely recommendation will be generated to on the exhaust fan to control temperature and on the external misters to make sure the humidity levels are not affected. If CO2 level increases than the required levels, the timely recommendation will be generated to on the exhaust fans to maintain CO2 and on the external misters to make sure humidity and temperature levels are unaffected.

Receiving the notification at the correct time enables them to manage the resources inside their mushroom farm by working as they see fit. This comes from other types of algorithms, but here using this LSTMs algorithm can be used to reach a higher level of accuracy level.

2 *Mushroom Harvest Time Identification*

A dataset containing 1887 images in total was collected at 05 different stages of a mushroom life from two agro-processing mushroom farms. The images collected to create the dataset were captured using a phone camera consisting a resolution of 4160 * 3120 pixels. The five stages are displayed with one of its respective images in Figure 5:

The user data is passed through an API into the Convolutional Neural Network (CNN) model that runs to obtain the harvest time of mushrooms.

To train the collected data a CNN was used. Substantially, in order to achieve real time predictions and accurate results the Mobile Net Version 2 model of CNN was applied. CNN was constructed based on the concept of an human brain architecture [16]. CNN embody particular nodes called neurons and they are arranged onto different layers. The Mobile Net Version 2 performs significantly

Figure 5 : Stages of mushrooms from growing, harvesting to post- harvest phase

on mobile devices [16]. Therefore, it is used for its effectiveness in feature extraction.

The model of the proposed system was created using CNN with the Mobile Net Version 2 model. Applying transfer learning, the image sizes were resized into a uniform resolution of 224 x 224 and normalized [17]. Then the RGB images were converted into grey images. Creating the model, Mobile Net Version 2 was used with an input shape of 224 x 224 using 03 channels. A new model was created and sutured into CNN [17]. The rest of the model was constructed by adding the required layers. Average pooling layer, of pooling size 4 x 4 to down sample its input images by taking the average value over an input window of pooling size. Flatten layer, to transform data into a one-dimensional array to pass onto the next layer. Dropout layer, to reduce over fitting by preventing complex co-adaptions of training data. The dense layer, being a fully connected layer completes the classification. To train the data 20 epochs were used in order to train it 20 times to get an accurate result. The model was tested after the data was trained using the created model After the data was trained using the created model, the model was tested. For testing out of 1887 mushroom images 80% was used for training and thereby 20% was used for testing.

Using this part of the research, the farmers are alerted when to harvest their mushrooms, their suitability for consumption and the expiry date. The farmer needs just to capture an image of the required mushrooms through the mobile application and then to let the application to analyze the image for them and then alert them with the detected harvest time.

3 *Identification of diseases and recommendation on appropriate remedy*

A dataset containing 710 images in total was collected of 05 different types of diseases which are likely to grow in a mushroom cultivation from two agro-processing mushroom farms. The images collected to create the dataset were captured using a phone camera consisting a resolution of 4160 * 3120 pixels.

There are 5 main identified Oyster Mushroom diseases on cultivation bag and mushroom bud that are most available in Sri Lanka as shown in Figure **??**. Convolutional

Figure 6 : Diseases on mushroom flowers and cultivation bags

Neural Network, a deep learning algorithm was used to diagnose Black Mould, Green mould and Mite Attack diseases and Image Processing method was used to diagnose Neurospora and Thali Makka attack.

The total of 710 images was used to identify the diseases of the mushroom. The images which include their symptoms are taken from two mushroom farms. The dataset carries 216 images as ‘Black Mould’, 268 images as ‘Green Mould’ and 226 images as ‘Mite attack’. The image which needs to be checked for diseases will be captured through the mobile application.

The best advantage of using Mobile Net V2 architecture is that it perform faster than a consistent convolution and more suitable for mobile applications. The architecture began with 3×3 convolution kernels and then progressed to 16 depth wise separable convolution blocks to offer a mobile model that is effective. The input images processed through several convolution layers, pooling layers and eventually a fully connected layer that displays the classification results as illustrated in Figure **??** [18]. The dataset

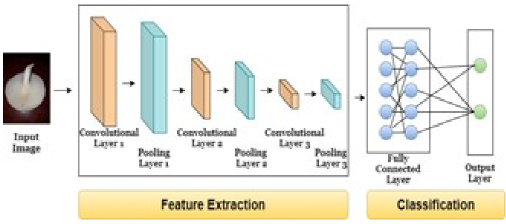


Figure 7 : CNN Architecture

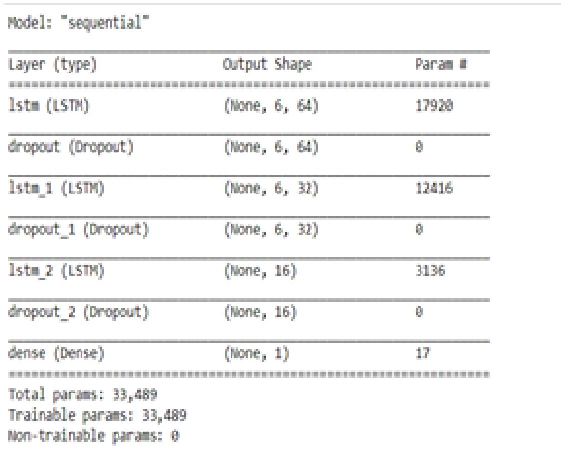
used average pooling layer with size 4×4 and 1280 neurons to reduce dimensions and spatial variance. To achieve more successful accuracy, the Dataset was trained to 100 epochs. [8]. Mainly, the disease is segmented according to an object in the image, depending on colour. The images come in three types: colour (RBG-Red, Green and Blue), grey and binary. In image processing the RGB images were transformed to the HSV colour format [23].

- Hue - The pure colours. It is distributed in a circle ranging from 0-180 in OpenCV.
- Saturation – Controls the amount of colour used with white.
- Value – Controls the brightness of the colour.

Numpy, a highly efficient library for numerical computations, is used by OpenCV-Python to process images and identify the objects[7]. The diseased image took a mask of the image and the range between the upper color and lower color of the mask was white, and the rest was black. The upper color is determined from the color of diseased image from the Hue values by getting the best range. The lower_colour varies with the upper_colour. Furthermore, using 'contour Area' can remove unwanted objects from the image.

4 *Harvest Prediction*

There is a lack in supply of mushrooms in the food market. This is due mushrooms' fluctuated production yield [20]. This functionality focuses developing a segment, which will notify the farmer through a mobile application regarding the yield of the mushroom cultivation at four stages of the cultivation based on the environmental factor conditions, mushroom harvested time and diseases that has spread. For this a dataset of 500 plus records with the manual monitoring of environmental factors, harvested times, and the presence of diseases from an oyster mushroom farm was collected. These data are passed through a RNN long short-term memory to forecast the production yield of mushrooms. Temperature, humidity, Co2 level, diseased, right harvest time & yield per day were monitored hourly for 12 hours a day their average values are obtained for each day. Then those values for 5 consecutive days are considered to estimate the total expected yield for particular month.



Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 6, 64)	17920
dropout (Dropout)	(None, 6, 64)	0
lstm_1 (LSTM)	(None, 6, 32)	12416
dropout_1 (Dropout)	(None, 6, 32)	0
lstm_2 (LSTM)	(None, 16)	3136
dropout_2 (Dropout)	(None, 16)	0
dense (Dense)	(None, 1)	17

Total params: 33,489
Trainable params: 33,489
Non-trainable params: 0

Figure 8 : LSTM Architecture

A RNN layer's output includes an individual vector per sample by default. This vector contains the information of the entire input sequence and it is the output of the RNN unit corresponding to the last time step. This output has the shape, where units is the unit's argument passed to the layer's constructor. Furthermore, an RNN layer can return its final internal state or states and the returned states can be used to resume the RNN execution or to start another RNN. This is a frequent configuration in the encoder-decoder sequence-to-sequence architecture, where the encoder final state is utilized as the decoder's initial state. Set the return state argument to True when establishing an RNN layer to have it return its internal state and there are 3 state tensors in LSTM [27].

Reasons for choosing LSTM over other techniques, because it's best suited for using experience to identify, analyze, and predict time series with unknown time lags. LSTM prediction technique was created to assist network operators in detecting and reacting to network traffic fluctuations in near real-time before they become congested. According to the findings, by many orders of magnitude, LSTM beats standard linear approaches and feeds forward neural network.

IV RESULTS

The trained models were tested on the test data to get the corresponding accuracies of classification of collected data from local mushroom farms through the developed IOT device and phone camera. The accuracies obtained are illustrated in Table 2.

Table 2 : Accuracy table

Function Name	Accuracy
Environment Factor monitoring(LSTM)	89%
Harvest Time Detection (CNN)	92%
Disease Detection (CNN)	99%
Yield Prediction (LSTM)	95%

The number of epochs committed is directly affecting the accuracies of the models. For the Environmental factor monitoring, Figure 9 displays the accuracy acquired in training the previously collected data using the model. Figure 10 displays the loss that occurred during the training. The Figure 9 and figure 10 plots explains an event of overfitting, since the validation loss decreases up to a certain point and increases and decreases again. By using more data to train the model it will be able to increase the accuracy more.

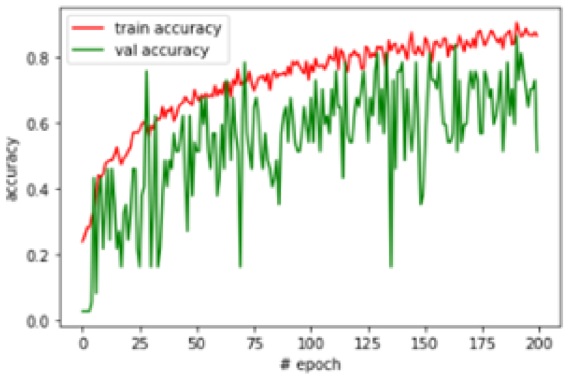


Figure 9 : Accuracy Graph for Environmental Factor Monitoring and Recommendation

The training accuracy of employing the CNN model for harvest time detection was 92% as shown in Table **??**. For the Harvest Time Detection, Figure 11 displays the accuracy acquired in training the images used in the model

For the Disease Detection, Figure 13 displays the accuracy achieved in training the images used in the model. Figure 12 describes the accuracy achieved in training the images used in the model for the harvest prediction. Figure 14 the loss that occurred during the training.

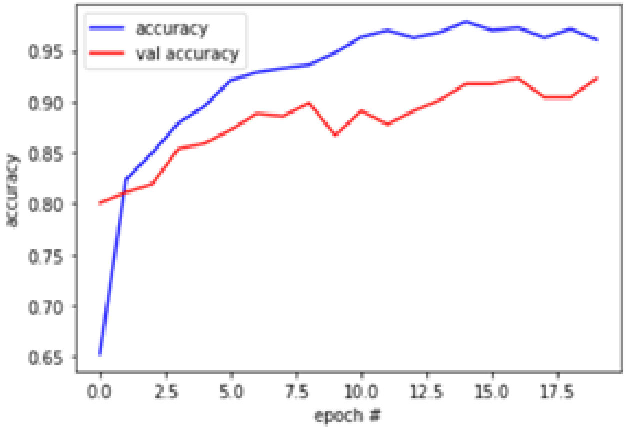


Figure 10 : Accuracy Graph for Harvest Time Detection

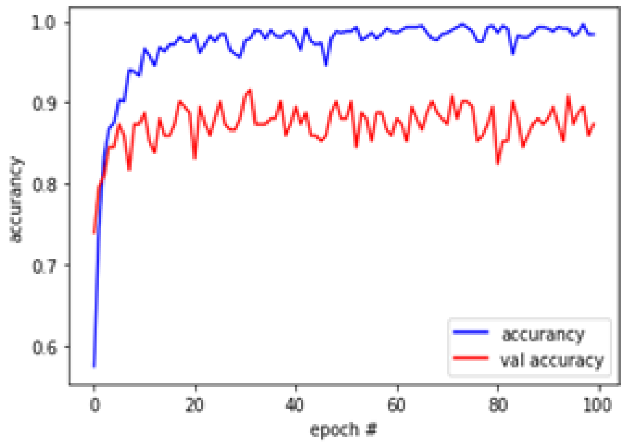


Figure 11 : Accuracy Graph for Disease Detection

The authentication system has the following accuracies of each function: The system analyzes and recommends environmental factor controls with an accuracy of 82%, Identifies the mushroom harvest time with an accuracy of 92% and detects the diseases within mushrooms with an accuracy of 92% and Predicts the mushroom yield with an accuracy of 95%. Validation accuracy linearly changing with the training accuracy indicates high accurate predictions of independent data. This indicates that the model was successful in memorizing the data.

V LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

This research's main limitation in scope of its functionalities was that the disease detection functionality limits for the detection of only five disease types.

This study can be further elaborated to develop the system to detect the disease spread within mushroom farms at early stage. Also further development could be done with a robotic arm to pluck mushrooms at detected harvest

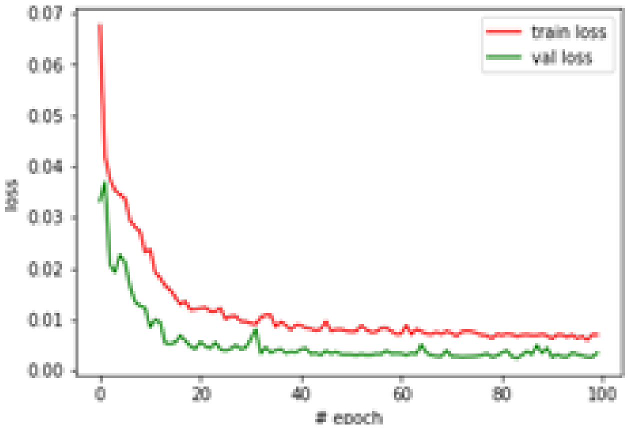


Figure 12 : Loss Graph for Yield Prediction

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test_r2_score: 0.9467178124464929
train_r2_score: 1.0
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Figure 13 : Accuracy of Harvest prediction

times using cameras place in the farm rather than capturing through the mobile phone for real time harvest alerts. Also the limited scenario of monitoring and providing control recommendations can be further developed to build a mechanism to control the factors using a control unit.

VI CONCLUSION

This paper presents a solution to the problems faced during mushroom farming in Sri Lanka. The solution presented comprise of four functionalities each serving a different issue faced. Identification of mushroom Harvest time and diseases are introduced to solve issues regarding the harvesting and disease spread within a mushroom farm house build based on a CNN model. The analyzation of environmental factors and providing a control recommendation functionality serves to solve the issue related in maintain farms climatic changes with the aid of an LSTM model. For the purpose of being able to serve the market demands farms yield is predicted to the farmers with the aid of LSTM.

Replacement of manual farming strategies with the designed technological farming approach farmers are directly benefited from achieving high yield in turn increasing their revenues. Thereby farmers expanding businesses, respective governments are benefited indirectly with taxation revenues. Buyers purchasing products grown under exact requirements receive high quality items.

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ABBREVIATIONS AND SPECIFIC SYMBOLS

- LSTM - Long Short Term Memory
- CNN- Convolutional Neural Network
- RNN- Recurrent Neural Network

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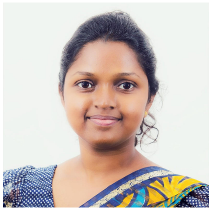

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