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Automation in Agriculture and Smart Farming Techniques using Deep Learning

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***Abstract*—Agriculture is considered to be a field of great importance and with a serious economic impact in all successful countries. Due to the substantial increase in world population, it has become a relevant concern to be able to meet people's daily dietary needs. Henceforth, it has become inevitable to make a transition to smart agricultural techniques to achieve the set food security goals. In recent times, several deep learning methods, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been vigorously studied, applied, and researched in different fields, including farming and agriculture. In this project, we aim at analyzing existing research on deep learning techniques in smart farming and agriculture and propose solutions for different aspects of farming using various deep learning architectures. Furthermore, we studied the farming parameters such as weather reports, plant irrigation information, pests that affect common crops, germination periods of the flowers/seeds, disease/anomaly detection in their leaves, etc., and proposed modular solutions for each of the respective areas of smart farming. Additionally, we also compared relevant studies regarding farming and focused agricultural methods, problems being faced, the method for collecting data being used, and the deep learning model suggested.**

***Index Terms*—Automation, Convolution Neural Networks, Deep Learning, Irrigation, IoT, Precision Agriculture, Smart Farming**

I. Introduction

Smart agriculture refers to a wide implementation and use of artificial intelligence and related methods that involve huge data, the internet of things (IoT), deep learning techniques, and scores of other emerging digital tools and technologies [1]. As the global population increases, a corresponding increase in grain/food consumption and production has to be ensured. Providing a constant source and maintaining optimum food quality globally without impacting existing ecosystems is demanding for modern-day technologies [2]. Deep learning is a modern technology that provides various methods for image processing and big data analysis. It has produced satisfying results, holds great potential, and has been successfully implemented in different fields, including farming and agriculture [3]. In recent times, deep learning-based farming and agricultural applications termed smart agriculture has gained remarkable success. This requires the management of different agro-economic processes using the data acquired from diversely placed sources. Different intelligent systems based on Artificial Intelligence differ subjectively in their aptness to analyze and explicate data and consequently aid the farmers in taking better decisions at the correct time of the germination period. This data can be collected using pre-installed IoT devices (sensors), followed by processing through a certain deep learning method, and determine and perform decisions on stochastic areas by means of actuators [5]. Other best-in-class technologies, such as detecting demographic data remotely, global satellite positioning(GPS Systems), and sensor-based automated data collection, simulate the AI sub-system in observing and monitoring agricultural activities in near real-time.

Additionally, AI-based smart farming/agriculture can be availed to perform optimal resource allotment, e.g. pesticides, fertilizers, and water for irrigation purposes, thereby reducing pollution level and operational/setup costs and increasing production value. As artificial intelligence can help in the timely identification and thwarting of plant/leaf diseases, reducing their spread, and would need fewer drug remedies, consequently reducing pollution to a great extent [9]. The continuous and regular supply of agronomic utilities, like nutrients, water, and pesticides, is crucial for plant growth, health, and overall yield. The uncertain absence of one or more of these inputs may lead to biotic and abiotic strain on plants. The judgment to apply the appropriate quantity of a specific utility at the appropriate time by observing the existing situation and predicting the future is only feasible through AI-Based Systems. This project studied and recorded the utilization of these AI techniques and deep learning methods in agriculture and its future potential in smart farming applications. The research also looked upon the agricultural parameters observed by IoT sensors and used those to provide input to the deep learning algorithms(training data collection) for further decision-making. This research discusses a series of developed systems in smart agriculture using deep learning techniques and digital algorithmic tools. The motivation for taking up this project originates from the importance of deep learning techniques and innovative applications that these methods can bring about in solving farming-related problems. The use of these deep learning methods in smart agriculture is comparatively new and in the process of widespread adaptation and is consistently gaining popularity in recent research works [4]. Therefore, valuable contributions made by these techniques to look up the issues of smart farming in data modeling and governing scenarios have been highlighted. This paper presents, through a series of modules, a robust set of systems to observe, record, view, search and monitor crops in a field, determine whether they are suffering from diseases or not, determine the presence of pests, understand and evaluate weather information and finally suggesting a 1-3 way water irrigation routing module for autonomous irrigation pipeline.

The contents of this document are arranged as follows. The work and methodology are discussed in Section 2. Section 2 is divided into 6 sub-parts, discussing various proposed techniques for plant species detection, pest detection, flower detection, plant disease classification, 1-to-3 way water routing, and pests information collector. Section 3 presents experimental results and the inferences drawn from them. Finally, the future scope and conclusion of the research are provided in Section 4.

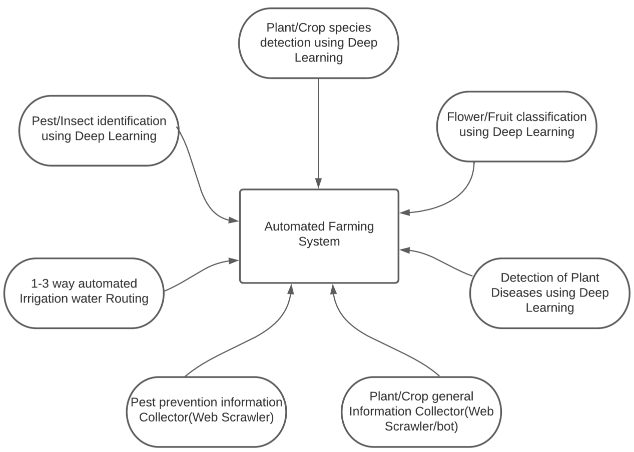

Fig. 1. Block diagram of all related modules

II. Methodology

A. Identification of plants/crops species

Species knowledge is very important for proper growth mechanism and management of a crop germination lifecycle. Henceforth, it becomes important that for an automated system, a plant species recognition sub-system needs to be prepared. This can be done in multiple ways.

When compared to conventional image recognition systems and commonly used image processing techniques, deep learning is quite different. In CNN, we do not need to extract specific features, rather the feature extraction takes place through the iterative learning process, which is in itself capable of capturing necessary image features. [6]. Henceforth, for detecting plant species, a Faster RCNN Inception V2 model has been trained. Faster RCNN is an object detection-based architecture, that was introduced in 2015, and is one of the most popular object detection architectures that are based upon CNN. The basic architecture of Faster RCNN comprises 3 building blocks, the Convolution Layers, the Region Proposed Network, and Bounding Box prediction. [7]

B. Pest detection/classification in crops

Pest recognition in farming and agriculture has great importance for farmers and is the reason for diminishing growth. Up till now, only conventional techniques were being used by the farmers to control the pest population and increase their total crop yield [10]. But, with the advent and success of deep learning technologies and their application in agriculture, researchers now are attempting to use deep learning tools such as Convolution Neural Networks (CNNs), to be able to recognize different pest species using computer vision, and hence move towards developing a robust, automated pest detection and control system, for better farm productivity. Hence, for the classification of pests, we propose to use a transfer learning technique and train an AlexNet Deep Neural Net [12].

AlexNet is a state-of-the-art Convolution Neural Network, which is 8 layers deep. The basic structure of the neural network contains three parts, the Convolution layer, the Max Pooling layer, and the Fully connected layer. The AlexNet network contains about 60 million parameters, with a sum total of 650,000 single neurons.

The dataset used for training the model contains images of several different pest species, namely Nilavarpata Lugens, Pomacea Canaliculata, Pycularia Oryzae Neck Panicle, Stem borer larva, etc. In total, there are 3549 images available [13]. The dataset is then split into training and validation sets in the ratio of 80:20.

Once training of the images is completed, and the probabilities are generated using softmax classification, results for the method are plotted, and accuracy is observed by visualizing the confusion matrix.

C. Identification/Classification of Plant Diseases

Plant/crop disease detection is a crucial research topic in the field of computer vision and deep learning. It is a set of tools that make use of computer vision to gather images and decide whether the crop is suffering from any disease or not. Traditional plant disease detection methods include typical image processing techniques and the use of conventional machine learning algorithms that extract features and use classifiers to separate them into different categories. In complex, real-life environments, this particular process faces many different issues, like unclear images obtained, very small or no difference between contours or lesion area, unnecessary noise added to the images, and other kinds of disturbances. Furthermore, varying natural light conditions can also affect the quality of images captured and hence greatly alter the final result predicted.

For disease classification, a public dataset of 54,305 images of diseased and healthy plants has been used, that were monitored and collected under controlled conditions, (Plant Village Dataset). After downloading and importing, the dataset is segregated into training and validation sets in a 1:4 ratio. The research use Inception V3 pre-trained model to classify plant leaves into different classes. The learning rate for the model is specified as 0.001, in order to keep the training duration under wraps, only 5 epochs were considered. Also, the optimizer used in the training procedure was the Adam optimizer, and "categorical_cross-entropy" is used as the loss function.

D. Fruit/Flower species recognition system

Flowers have been proven to be very beneficial to humans in many areas. They are consistently in demand in the Cosmetics and Pharmaceuticals industries. Yet, it is a considerably difficult task to differentiate between them due to their similarity in shapes and colors. A good understanding of flowers is essential to be able to recognize new or very rare species whenever encountered. Hence, as the classification of flowers is an important task, several types of research have been conducted and different approaches have been developed by researchers. Conventional methods include the use of histograms, scale-invariant features, and non-linear classifiers to classify different flower species. However, with the advent of Deep Neural networks, and successful applications of CNNs in object detection and classification use cases, it has become imperative to use these techniques to produce better results. Hence, in this research, for classifying flowers in plants, an Xception model architecture was prepared using a modular and efficient deep learning python package "Keras".

On looking at the datasets, FLOWERS102 and FLOWERS17 datasets [9], from the Visual Geometry Group at Oxford University, were used to train and test the algorithms. The model is trained for 20 epochs and the performance is thus analyzed by plotting accuracy vs epochs and loss vs epochs plots.

E. Weather Information Collector

Weather information plays a very crucial role in agricultural activities, as it can directly affect the schedule and intensity of day-to-day activities. Also, it is important to be in control of the information about current and upcoming weather, and how will it affect the crops.

Agriculture is very easily impacted by climate change. For example, higher temperatures in the fields will eventually affect the net crop production and cause a reduction in the yield. Furthermore, this also poses a risk of an increase in weed and pest populations. Rapid fluctuations in the precipitation (rain) patterns can also increase the probability of crop failures, and in the long term cause a decline in crop produce [14].

With a significant increase in digital technologies, it is imperative, that we use information systems available to determine current weather forecasts and prepare the countermeasures accordingly. So, as part of this project, a weather information collector bot has been prepared. This is essentially an automated piece of code, that displays important weather information of a place, by taking its location (geographical location) as input. It uses the open-source api platform "openweather api", in order to fetch weather information by just entering the location of the field. It further returns the following parameters as output, which are of significant importance in agriculture:

• Pressure • Humidity • Average temperature • Max and Min temperature • Visibility • Wind speed • Sky condition(cloudy, clear, overcast, etc.)

F. 1-to-3 Way Irrigation water supply Module

In recent years, with the increasing population and rapidly changing climate, there has been a scarcity of water supply for agricultural purposes. Almost 85% of all the water used in farming is for the purpose of irrigation to the crops. Additionally, wastage of water has also become a serious problem that needs to be taken care of [8]. Hence, there is a major need for water management techniques and better irrigation practices. It is important to modernize traditional irrigation systems for better resource conservation. The use of automated irrigation systems is one of the ways, with which an adequate quantity of water can be provided on a real-time basis. Also, different crop belts have different requirements, hence having the capability to control the supply through automated signals, would lead to better control and management of water supply. Hence one of the ways we propose to achieve this task is through an automated 1-3 way routing system. This system aims at taking a single water supply source and routing the water to any of the three irrigation gates, as per the requirements.

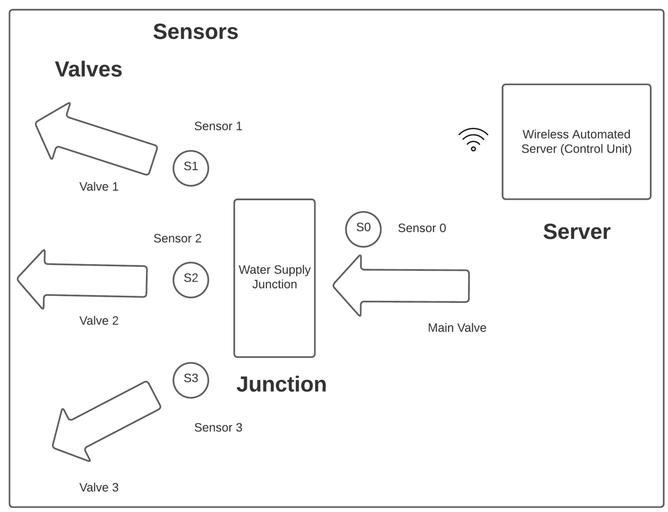

Fig. 2. 1-to-3 way Routing architecture block diagram

G. Pest Information Collector (Web Crawler)

Web Crawling software dates back as the World Wide Web goes. These are mostly short scripts and individual codes that are also commonly known as bots or worms [14]. Their objective is to parse and download webpages, take out the useful data, extract all the links, and store these extracted data in a structured manner e.g. a database. In this research, our aim is to create an automated bot, that is capable of scraping existing online public databases, containing information about pests, their basic identification techniques, their related images, the extent of damages they can cause, particular suggested remedies, and solutions to prevent them from spreading further.

III. Results and Discussion

A. Crop species identification/classification

The process for determining the plant species is divided into multiple steps. For keeping the training time in bounds, the model was trained on only 20 epochs. The model is being trained in the Tensorflow environment, using Keras, python, and the graphs are plotted using Matplotlib. For evaluating the performance, the model was trained on multiple datasets like the Flavia dataset, Swedish leaf Dataset, LeafSnapp dataset, and MalayaKew dataset. The model reaches a training accuracy of 95.38%.

The training accuracy and validation loss plot are shown below in Fig 3.

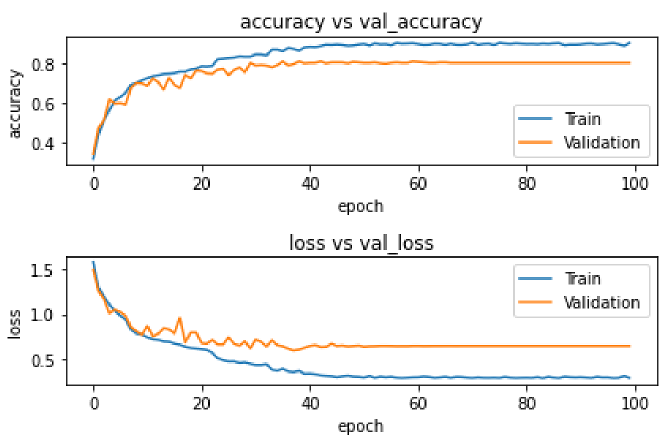

Fig. 3. Accuracy and Loss curves for Crop Species detection

B. Flower species recognition

The proposed system based on the Overfeat network architecture is trained on FLOWER17 and FLOWER102 datasets, as discussed in the above sections. In the same, it is able to achieve a Rank 1 accuracy of 72.05% and Rank 5 accuracy of 91.32%. Further, data for training the same dataset on Inception v3 and Exception architectures are also presented to do a comparative study.

TABLE I
Different CNN architectures in flower recognition

Dataset	Model	Rank-1 accuracy	Rank-5 accuracy
FLOWERS17	Inception- V3	92.41	98.66
	Xception	90.18	98.66
	Overfeat	84.36	98.93
FLOWERS102	Inception- V3	93.41	96.42
	Xception	90.60	94.16
	Overfeat	72.05	91.32

From the data given in Table 1, it can be observed that the accuracy of the model can be improved greatly by using a more deep architecture. The recognition accuracy increases with the increase in the number of layers in the CNN.

C. Plant disease detection

Once the training process of the proposed architecture is complete, the training accuracy is determined. The results showed that the overall accuracy of identifying the diseases in plants was about 98.26 % at the leaf level. The validation accuracy for the model also stood at 96.77 %, referencing that the trained architecture, produces significantly accurate results in classifying the diseased plants.

Further. The test accuracy is also determined using the evaluate method, which was observed to be 96.7738%. The training and validation curves w.r.t the epochs are then plotted as shown in Fig 4.

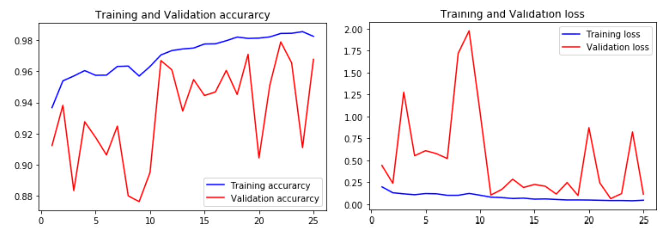

Fig. 4. Training accuracy and Validation loss curves for plant disease detection

D. Pest/Insect detection

The accuracy of the trained model has to be determined to check its effectiveness. We use the conventional equation, given by [16]. In this equation, true positives are the number of samples that are positive and are also predicted as positive, the true negative is the number of samples that are negative, and are predicted as negative too.

A training accuracy of 91.13% was observed in the AlexNet model, with a validation accuracy of about 90.27%. Several pre-trained model accuracies were also compared with our model, which was also trained on the same dataset. When compared, GoogleNet showed a training accuracy of 92.2% along with a validation accuracy of 91.2%. At the same time, ResNet50 architecture showed a promising validation accuracy of 90.03%, with a validation accuracy of 90.02%. The Fine-tuned ResNet50 network, had an improvement over its predecessor, with a training accuracy of 94.03% and validation accuracy of 92.11%. The confusion matrix, depicting the predicted classes for the pests dataset is shown in Fig 5.

E. Weather Information Collector

The bot was created using Python 3.8, and an open API “openweather API” service, to determine weather data using location information. Other libraries used include NumPy, Pandas, and Openpyxl, for storing the data in an excel file. The information parameters that are recorded include temperature, average temperature, min-max temperature, humidity levels, air pressure, precipitation rates, and sky conditions. Fig. 6 below, demonstrated the fetching of information for Gwalior city, Madhya Pradesh, India.

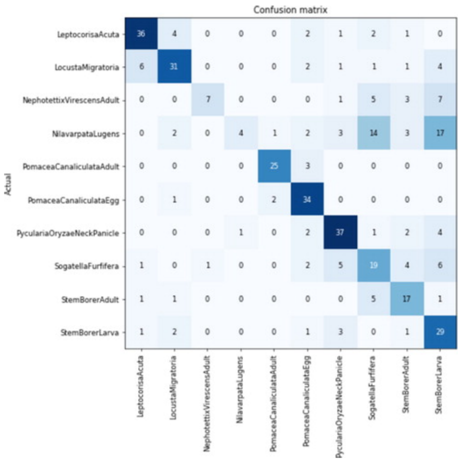

Fig. 5. Confusion matrix for classification of pests in different classes

Enter Your Location: gwalior
http://api.openweathermap.org/data/2.5/weather?q=gwalior&APPID=5f7db2b9750325996fd091f5f6d6d78b
{'base': 'stations',
 'clouds': {'all': 98},
 'cod': 200,
 'coord': {'lat': 26.2236, 'lon': 78.1792},
 'dt': 1659246736,
 'id': 1270583,
 'main': {'feels_like': 311.29,
          'grnd_level': 979,
          'humidity': 47,
          'pressure': 1002,
          'sea_level': 1002,
          'temp': 307.5,
          'temp_max': 307.5,
          'temp_min': 307.5},
 'name': 'Gwalior',
 'sys': {'country': 'IN', 'sunrise': 1659226324, 'sunset': 1659274508},
 'timezone': 19800,
 'visibility': 10000,
 'weather': [{'description': 'overcast clouds',
              'icon': '04d',
              'id': 804,
              'main': 'Clouds'}],
 'wind': {'deg': 284, 'gust': 5.75, 'speed': 5.57}}

Fig. 6. Recorded parameters from Weather Information Collector bot

IV. Conclusion

In this research, our aim was to develop a robust set of tools that can be used in coordination with each other and implore the use of deep learning, IoT, and other digital technologies in agriculture automation and smart farming domains. Our observations clearly indicate that deep learning and its related methods produce a better outcome in almost all categories of its application. Moreover, it also offers a higher level of accuracy as compared to existing conventional techniques. In addition, we also proposed web-crawling bots for the collection of useful information related to crops/plants, for better planning and crop management. This work is helpful for engineers and budding researchers who are looking to experiment in the field of smart agriculture and can study and apply the discussed deep learning techniques to their own classification or identification problems.

References

[1] Altalak, Maha & uddin, Mohammad Alajmi, Amal Rizg, Alwaseemah. (2022). Smart Agriculture Applications Using Deep Learning Technologies: A Survey. Applied Sciences.

[2] V. Puranik, Sharmila, A. Ranjan and A. Kumari, "Automation in Agriculture and IoT," 2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU), 2019.

[3] Kamilaris, A.; Prenafeta-Boldú, F.X. Deep learning in agriculture: A survey. Comput. Electron. Agric. 2018, 147, 70–90. [CrossRef] 5. Ren, C.; Dae-Kyoo, K.; Jeong, D. A survey of deep learning in agriculture: Techniques and their applications. J. Inf. Processing Syst. 2020, 16, 1015–1033.

[4] Sharma, A.; Jain, A.; Gupta, P.; Chowdary, V. Machine learning applications for precision agriculture: A comprehensive review.

[5] Vinayak N. Malavade1, Pooja K. Akulwar2, 'Role of IoT in Agriculture', National Conference On "Changing Technology and Rural Development" CTRD 2k16, SGI, Atigre, India. IOSR Journal of Computer Engineering

[6] Naskar, Avijit & Mandal, Akrito & Ghosh, Anirudha & Saha, M & Sufian, A.. (2019). Convolutional Neural Networks.

[7] Ghoury, Shekofa & Sungur, Cemil & Durdu, Akif. (2019). Real-Time Diseases Detection of Grape and Grape Leaves using Faster R-CNN and SSD MobileNet Architectures.

[8] Rathika, S., T. Ramesh, V. Priyadharshini, A. Suriya Prasanth and Shanmugapriya, P. 2020. Automation in Irrigation - A Review. Int.J.Curr.Microbiol.App.Sci.

[9] L. Li, S. Zhang and B. Wang, "Plant Disease Detection and Classification by Deep Learning—A Review," in IEEE Access, vol. 9

[10] V. Malathi & M. P. Gopinath (2021) Classification of pest detection in paddy crop based on transfer learning approach, Acta Agriculturae Scandinavica, Section B — Soil Plant Science,

[11] Ives, Zachary. "Notable CNN Architectures." CIS 545 Big Data Analytics, 18 Nov. 2020, University of Pennsylvania. Microsoft PowerPoint presentation.

[12] Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton "ImageNet Classification with Deep Convolutional Neural Networks" Advances in Neural Information Processing Systems 25 (NIPS 2012)

[13] Alfarisy AA, Chen Q, Guo M. 2018, April. Deep learning based classification for paddy pests diseases recognition. In: Proceedings of 2018 International Conference on Mathematics and Artificial Intelligence. p. 21–25.

[14] Nemeslaki, András Pocsarovszky, Károly. (2011). Web crawler research methodology.

[15] Gornall Jemma ,Betts Richard, Burke Eleanor ,Clark Robin, Camp Joanne, Willett Kate and Wiltshire Andrew 2010 Implications of climate change for agricultural productivity in the early twenty-first century.

[16] Alfarisy AA, Chen Q, Guo M. 2018, April. Deep learning based classification for paddy pests diseases recognition. In: Proceedings of 2018 International Conference on Mathematics and Artificial Intelligence.