A Convolutional Neural Network-Based Plant Pesticide Recommendation System for Rural Areas

Mrs.Kawsalya. S[1] Bala Krishnan N[2] Deena Dhayalan R[3]
[1]Assistant Professor [2,3]Student
[1,2,3]Department of B.Com IT
[1,2,3]Nehru Arts and Science College, Coimbatore, India

Abstract — Problems with crop production are widespread in India and have a significant impact on the country's economy, particularly on rural farmers. Depending on the state of the leaf, farmers may predict the amount and quality of their harvest in advance, making the leaf an essential component of crop management. In this study, we provide a system that uses Tensor Flow technology for preprocessing and feature extraction of plant village dataset leaf pictures, then a convolution neural network for illness classification and pesticide recommendation. Our solution primarily makes use of two processes: deep learning and an Android app that makes use of Java Web Services. We trained our model using a Convolution Neural Network with five, four, and three layers, and we interfaced it with a user-friendly Android app and JWS. We found that a 5-layer model utilizing tensor flow attained the best accuracy at 95.05% after 15 epochs, and the maximum validation accuracy at 89.67% after 20 epochs.

Keywords: Plant Pesticide Recommender, Convolution Neural Network, Crop Production, Rural Farmers, Agriculture Sector, Leaf Images, Preprocessing, Feature Extraction

I. INTRODUCTION

Humans are able to increase their food production with the assistance of technology. Environmental factors, disease outbreaks, soil fertility, and other unforeseen events may all have an impact on food output. Of them, diseases have the greatest impact on food production [1]. The Indian economy is heavily reliant on the agricultural sector. Damage to trees and shrubs may be caused by leaf spot diseases because these diseases disrupt photosynthesis, which is essential for plant development, defense mechanisms, and survival. The majority of smallholder farmers rely on agriculture for their living, accounting for more over 58% [2]. More than 80% of food production in poor countries comes from smallholder farmers, and it's not uncommon for them to lose 50% of their produce to pests and illnesses [3]. One of the many reasons contributing to the steady decline in output is the difficulty in detecting plant diseases in their early stages [4]. Previous years have seen a wide range of activities. Dheeb Al Bashish, developed a system that uses device-independent transformation, image processing, and color space to identify the type of plant disease [5]. Bacterial diseases rapidly stunt plant growth. By using ANN and K-means to categorize and rank diseases, we can detect them early on and provide solutions to minimize damage, allowing us to boost agricultural yields. A system that can automatically identify leaf diseases and suggest the best insecticide to use is urgently required [6].

The overall rate of agricultural equipment utilization is believed to be lowest in south-eastern India. In regions where industrial crops are grown, Iran's output has fallen sharply and even halted due to inefficient labor [7]. Intelligent farming, sometimes known as "crop production," is an additional approach to modern agriculture that aims to address this issue. Farms may be made more efficient and productive with the use of intelligent devices [8]. The same farm's quality, the quantity of profitable goods, and the precision of cash payments to manufacturers are all guaranteed by several different methods [9].

Agricultural production data, GPS-assisted field modeling, fertiliser advice using worn-out equipment, and climatic data are all influenced by soil nitrogen availability, and this helps people understand that [10]. This data can help producers figure out which regions are the best for their products. Utilized in agricultural sectors include light technologies, computer sensors, information research technologies, communications networking (including portable, telematic, position breakthrough, and other self-contained detecting structures) [11]. Among the few countries that can boast four or five harvests year, India is right up there. Fertilizer management is something that Asian farmers are familiar with, although progress depends on soil ecology, common sense, and other factors. [12]. In contrast, producers now face great challenges, such as price rivalry among large firms and other factors that restrict production budgets and cause unnecessary hardship. The most current quarterly socioeconomic assessment of the same Hindu public sector, estimates that producers' livelihoods may be hit by 25-30% in a very short period of time due to climate change [13]. The research suggests that weekly producer sales would fall by around 4.5 percent [14]. Algorithms that include context in making recommendations are known as situational recommendation algorithms. Despite their inaccuracies, these research give helpful suggestions [15-16]. Soils, plants, types of soil, sunshine, minerals, compounds in the soil, pH levels, and the amount of water needed are all factors in the study [17–18]. Suggestions may be based on things like crops and environments, which is usually a good starting point for making the right choice. Agricultural civilization requires, among other things, discipline, security, and good sense. Current technical developments, on the other hand, have hardly registered in the agricultural sector [19–20].

II. BACKGROUND STUDY

A, P., Chakraborty et al. [1] these authors research method used by these authors aids farmers in making informed decisions about which crops to plant, lowering the likelihood of crop failure and raising yields. It prevents them from becoming bankrupt as well. In the future, the author want to build a web interface and a mobile app to help millions of farmers around the nation with crop production.

Banerjee, G. et al. [3] an effective and robust crop recommendation system that considers soil properties, rainfall, and topographical pattern was the goal of this authors' study for the Indian state of West Bengal. A cultivation index was the outcome of the dataset, which takes eleven soil attributes, land elevation, and annual mean precipitation as inputs. The membership functions that were utilized for input and output were created using the dataset. Eight major crops grown in West Bengal have had their system's performance tested. Comparatively, the system's average accuracy of 92.14% was higher than that of comparable modern systems. The increased economic production was a direct outcome of farmers' improved ability to make informed decisions about which crops to plant.

Jin, Z. et al. [7] In order to implement variable rate N fertilisation in the American maize system, these authors' study resulted in a prescription tool at sub-field scale. The suggested device used crop model simulations to track various soil N processes, establish management zones, train the model, and assess the growth state of crops. This approach successfully captured the sub-field variety of agricultural systems in a case study. In order to avoid overfertilization in areas with low yield potential, the suggested sidedress N rates raised yield potential in areas with high yield potential. The marginal advantages of sidedressing decreased as the quantity of fertilizer increased. According to a model sensitivity study, the authors' sidedress N guidance technique relied heavily on soil organic carbon concentration and soil hydrodynamic parameters. Calibration of the phenology module using normalized satellite-derived LAI allows for fine-grained management of crop N absorption during sidedressing. With less input from users up front, this authors' method outperformed existing N recommendation algorithms in terms of efficiency, accuracy, and scalability.

Kulkarni, N. et al. [9] Using the soil information in relation to the four crops—rice, cotton, sugarcane, and wheat—a crop recommendation method has been developed. Prior to using the ensembling approach to classify the four crops, the soil data was preprocessed. The ensemble model makes use of individual base learners such as Linear SVM, Random Forest, and Naive Bayes. The Majority Voting Method was chosen as the most precise combination approach.

Lacasta, J. et al. [11] a paradigm for characterizing crop outbreaks induced by pests and recognized pest-treatment options was introduced in this authors' study as the PCT-O ontology. The PCT-O ontology allows for the characterization of their interrelationships, unlike any of the other ontologies that define taxonomies of living beings. To put this ontology to use, the author suggests a recommendation system that may help find pests that were harming a particular crop and the answers to those problems. Official Spanish data on crops, pests, and authorized treatments has been added to the ontology.

Liu, K. et al. [13] All nine locations were used to evaluate the yield stability and crop output of certain oilseed crops and cropping methods. When compared to B. napus, B. juncea showed minimal volatility and great yield potential at the crop level, suggesting it might be a good alternative for oil seed cropping systems looking to diversify and stabilise production. Switching out lentils for more traditional oilseeds like wheat or fallow might significantly enhance system productivity; the lentil-oilseed showed a 33% increase compared to wheat-oilseed and a 112% increase compared to fallow-oilseed. The addition of crop and environmental interactions to dynamic stability makes it a more complete tool for evaluating system stability than static stability alone. According to the results of the combined static and dynamic stability assessment, the lentil-oilseed sequence performed better than the fallow- or wheat-oilseed sequences. Among the five oilseed-based cropping sequences, the one based on B. napus and B. juncea had the maximum yield stability. When trying to find the best cropping order for a given environment, it's important to think about both yield potential and stability.

Rajeswari, A. et al. [15] to aid farmers in their crop selection decisions, these authors used a fuzzy-based rough set method in their study. The author put the suggested method through its paces with twenty-four distinct crops—including Black Gramme, Maize, Cotton, Pearl Millet, Banana, Mulberry, Grams, millets, and paddy—and sixteen distinct input characteristics—including pH, EC, OC, magnesium, zinc, sulfur, copper, iron, and so on. Location, soil type, and pH were the three most important factors in determining the crop for a given area. The suggested method makes use of Fuzzy Logic to handle boundary situations when numerical characteristics were separated. A set-based rule induction method was used to formulate the fuzzy rules. Three or five MF language phrases were used in the suggested strategy.

III. Materials and Methods

A. Project Workflow

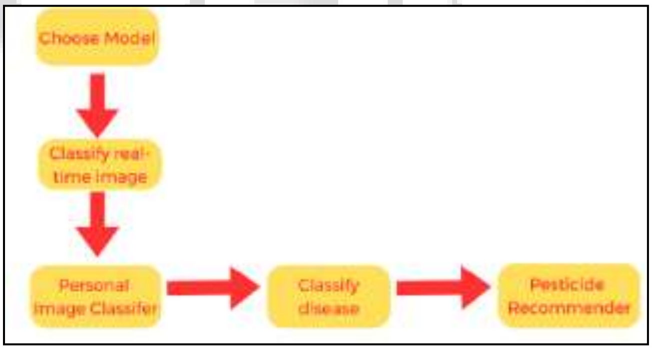

Fig. 1: Project Workflow

B. Feasibility Analysis

During this stage, we assess the project's viability and provide a business proposal outlining the project's broad strokes and rough budget. Conducting a feasibility assessment of the proposed system is an essential part of system analysis. To make sure the planned system won't be a financial strain on the business, this is necessary. A basic familiarity with the system's primary needs is necessary for conducting a feasibility study.

C. Economical Feasibilty

The monetary effect of the system on the company is what this research is trying to determine. Research and development of the technology may only be funded to a certain extent by the corporation. There has to be a rationale for the spending. Since most of the technologies used are publicly accessible, the constructed system was also able to stay below budget. It was necessary to buy just the personalized items.

D. Technical Feasibility

The technical requirements, or viability, of the system are the focus of this research. The designed system shouldn't put a strain on the current technological infrastructure. The current technological resources will be put to heavy use as a result of this. Because of this, the customer will face a great deal of pressure. Minimal or no adjustments are needed to implement the designed system, hence it must have a modest demand.

E. Social Feasibility

One goal of the research is to find out how satisfied users are with the system. This entails teaching the user how to make the most of the technology. The system shouldn't make the user feel threatened; rather, they should embrace it as an essential tool.

The techniques used to familiarize the user with the system and educate him about it are the only factors that determine the degree of acceptance by the users. As the system's end user, he needs to feel more comfortable providing feedback in the form of constructive criticism.

F. Operational Feasibilty

How well, enthusiastically, and competently the stakeholders can use, back, and run the planned computer information system. Management, staff, consumers, and vendors are all considered stakeholders. System goals should be user-friendly, error-free, information-producing, and in line with the organization's objectives for the benefit of all stakeholders.

G. Convolutional Neural Network

An example of a Deep Learning technique, a Convolutional Neural Network (CNN) may take an input picture, assign learnable weights and biases to different parts of the picture, and then differentiate between them. A ConvNet, in comparison to other classification systems, needs much less pre-processing. Instead of having to manually construct filters for use in more rudimentary methods, ConvNets may learn them and their associated attributes.

The structure of a ConvNet is similar to the way neurons in the human brain are connected. Individual neurons may only respond to stimuli within this limited region of the visual field, which is called the Receptive Field. A network of these overlapping fields encompasses the whole visual field.

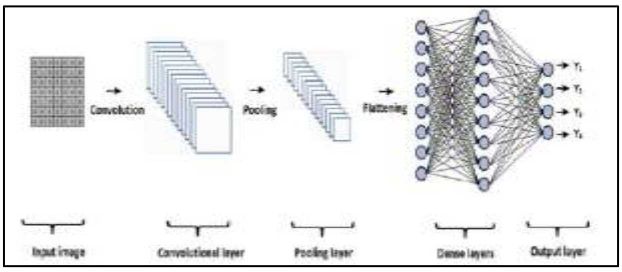

Fig. 2: Convolutional neural network architecture for plant leaf disease detection

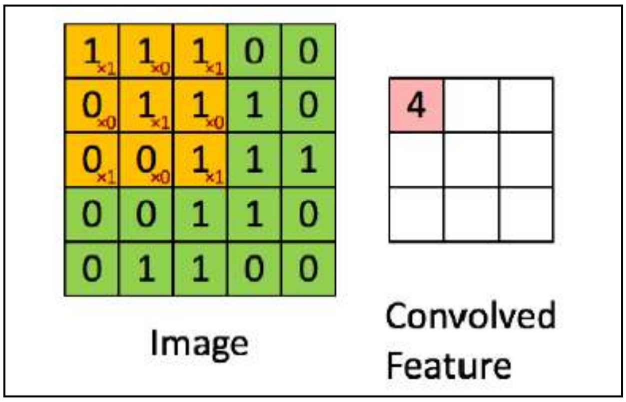

Fig. 3: Convoluting a 5x5x1 image with a 3x3x1 kernel to get a 3x3x1 convolved feature

In the preceding instance, the green region represents our 5x5x1 input picture, I. The yellow-colored Kernel/Filter, K, is the part of a convolutional layer that performs the convolution process in the first portion. The 3x3x1 matrix K has been selected.

Kernel/Filter, K =
1 0 1
0 1 0
1 0 1

Using the input image's edges and other high-level features, the Convolution Operation seeks to extract them. No specific number of convolutional layers is necessary for ConvNets. The initial ConvLayer usually takes a picture of the most basic elements, such as edges, colors, gradient directions, etc. We get a network that understands the pictures in the dataset holistically, similar to how we do, as the number of layers increases, and the architecture also adapts to the High-Level features.

1) Pooling Layer

Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature. Data processing power requirements may be met by dimensionality reduction. The ability to extract dominant features that are rotationally and position ally invariant also helps in training the model correctly.

There are two distinct kinds of pooling: maximum and average. Max Pooling returns the highest value from the picture region covered by the Kernel. Conversely, average pooling returns the mean of all the values from the picture region covered by the kernel.

In addition, Max Pooling may reduce background noise. Moreover, it eliminates all traces of the noisy activations after de-noising them.

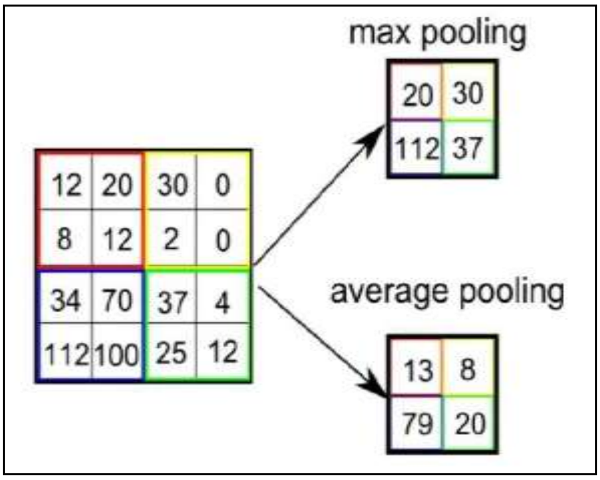

Fig. 4: Pooling Layer

The i^th layer of a Convolutional Neural Network is comprised of the Pooling Layer and the Convolutional Layer. To better capture low-level features, the number of such layers may be raised; however, this increases the processing power required, and is dependent on the complexity of the pictures.

Following the steps shown above, we were successful in assisting the model in understanding the characteristics. once that, we'll use a conventional neural network to classify the output once we flatten it.

H. About MIT Platform

Everybody, including kids, may use MIT App Inventor—a visual programming environment—to create fully working applications for tablets and smart phones. In less than half an hour, even someone completely unfamiliar with MIT App Inventor may have their very first app up and functioning. And unlike conventional programming environments, our blocks-based tool allows users to build sophisticated, high-impact applications in a fraction of the time. By giving everyone, but notably young people, the tools to go beyond just using technology to actually making it, the MIT App Inventor initiative hopes to level the playing field when it comes to software development.

Under the tutelage of Professor Hal Abelson, a small group of CSAIL faculty and students have emerged as the driving force behind a global innovation movement. This core group not only manages the free online app creation environment that over 6 million registered users rely on, but they also spearhead educational outreach initiatives related to MIT App Inventor and study its effects.

IV. RESULTS AND DISCUSSION

When assessing the practicality and consequences of the suggested system, the results and subsequent conversations around the project "Plant Pesticide Recommender Application for Remote Villages Using Convolution Neural Network" are of utmost importance. The part that follows provides a detailed analysis of the main findings, including the accuracy that was obtained, the results of the validation, and the wider implications of the technology that was built for dealing with problems in crop production in distant agricultural areas.

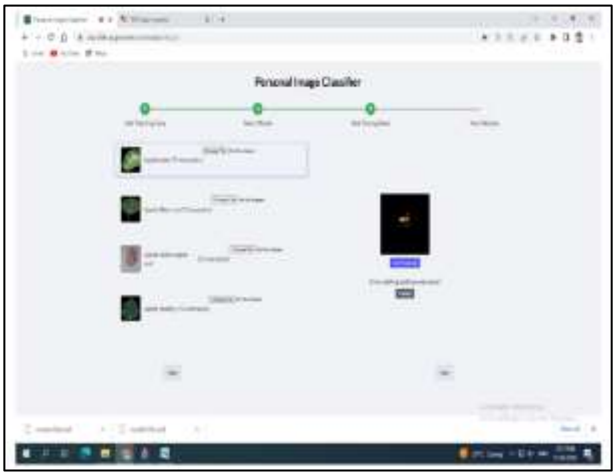

Fig. 5: Add the data set for the model and click train

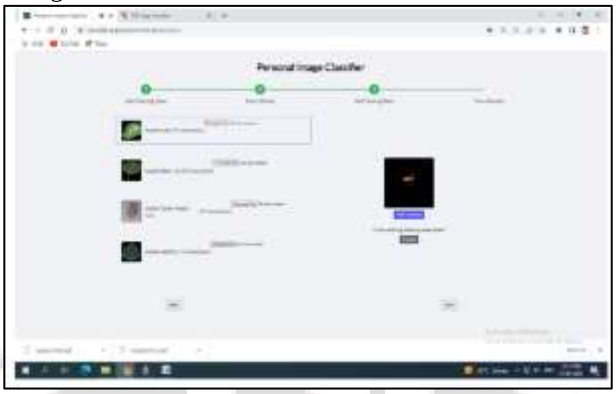

Fig. 6: Choose the model requirement and edit the hyperparameters as per the need

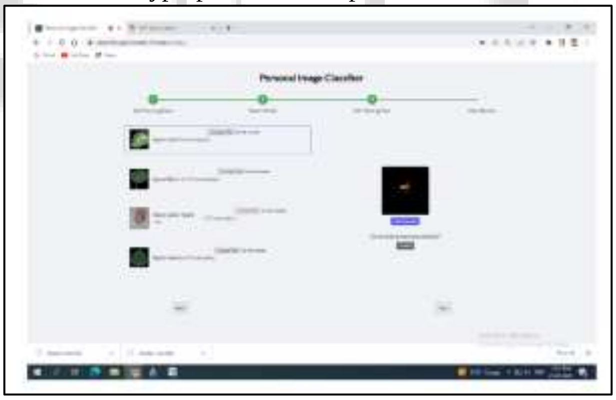

Fig. 7: Model accuracy testing and improving the accuracy

Fig. 8: Downloading the most accurate model developed and integrating with the Front End

V. Conclusion

To sum up, the "Plant Pesticide Recommender Application for Remote Villages Using Convolution Neural Network" is a huge step forward in helping rural farmers in India overcome their obstacles. Utilizing state-of-the-art technology like Tensorflow and Convolutional Neural Networks (CNN), our suggested system successfully diagnoses illnesses from leaf photos and suggests suitable pesticides. A user-friendly interface is provided by integrating an Android app with Java Web Services. This allows for smooth interaction between the deep learning model and end-users. The obtained outcomes demonstrate the resilience of our method, with a maximum accuracy of 95.05% for the 5-layer model. The system's dependability for real-world deployment is further validated by the validation accuracy of 89.67%. By aiding in the early diagnosis of crop illnesses and providing farmers with practical advice, this app boosts crop output, agricultural sustainability, and economic well-being in outlying communities. This project's fruitful fusion of technology and agriculture paves the way for effective and scalable solutions to strengthen agricultural communities' ability to withstand threats to crop output.

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