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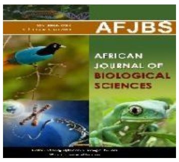

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Revolutionizing Agriculture: A DL Approach for Enhanced Plant Disease Detection and Classification

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Abstract

The agricultural sector stands as the cornerstone of a nation's innovative growth, playing a pivotal role in providing sustenance and raw materials. The critical importance of agriculture as a primary food source underscores the pressing need for effective plant disease identification. Traditional methods, reliant on subjective visual inspection by agriculture professionals or plant pathologists, have proven to be time-intensive and resource-demanding. So, this study introduces a technologically advanced solution by harnessing the capabilities of Machine Learning (ML) and Deep Learning (DL) for comprehensive plant disease detection and classification. The research leverages an experimentally evaluated software solution to address the limitations of conventional approaches. The proposed model integrates a sophisticated convolutional neural network (CNN) based on residual networks, facilitating robust feature extraction for accurate disease classification. Additionally, the study incorporates a preprocessing step to eliminate various types of noise with generic algorithm dependent Particle swarm optimization (GA-PSO) feature analysis, thereby enhancing the normalization of dataset images and improving the overall efficacy of the model. Building upon the success of the GA-PSO optimized Residual Network based CNN model in plant disease detection, this study extends its scope to include a novel aspect – pesticide suggestion, which is named GPR-CNN. The integration of pesticide recommendation systems into the framework aims to provide a holistic solution for managing identified plant diseases. Leveraging the same DL architecture, the model utilizes its learned features to suggest targeted pesticide interventions based on the specific disease detected. The simulation results underscore the efficacy of the proposed GPR-CNN model in not only achieving commendable accuracy rates in plant leaf disease detection and classification but also in offering precise and tailored pesticide suggestions. This innovative approach holds significant promise for revolutionizing agricultural practices, managing, and treating plant diseases. The seamless integration of plant disease detection and pesticide suggestion in a unified framework represents a significant step towards sustainable and technologically driven agriculture.

Keywords: Suggestions to Farmers, Plant disease classification, Image preprocessing, convolutional neural network, Convolutional neural network, agricultural innovation.

1. Introduction

Detecting and classifying plant diseases holds paramount importance in the realm of agriculture, serving as a pivotal tool in ensuring global food security, safeguarding crop yields, and sustaining agricultural economies [1]. The motivation for extensive research in this domain stems from the pressing need to address the multifaceted challenges posed by plant diseases, which have far-reaching implications on agricultural productivity, environmental sustainability, and human welfare [2]. First and foremost, plant diseases pose a significant threat to global food production and security. With a growing global population and escalating food demands, the occurrence of crop diseases jeopardizes the supply of essential food commodities, leading to shortages, price fluctuations, and food insecurity [3]. By accurately detecting and classifying plant diseases, researchers aim to mitigate yield losses, enhance crop resilience, and ensure a stable food supply chain to meet the demands of a burgeoning population. Moreover, the impact of plant diseases extends beyond agricultural productivity to environmental sustainability and ecosystem resilience [4].

Pesticides and chemical treatments employed to combat plant diseases often entail adverse environmental consequences, including soil degradation, water contamination, and biodiversity loss [5]. Consequently, there is a critical need to develop sustainable disease management strategies that minimize reliance on chemical inputs and promote ecological balance. Research in plant disease detection and classification endeavors to advance eco-friendly approaches, such as integrated pest management, biological control methods, and precision agriculture techniques [6], to mitigate the environmental footprint of agricultural practices. Furthermore, the globalization of trade and the interconnectedness of agricultural systems have exacerbated the spread of plant diseases across geographical boundaries [7]. The emergence of novel pathogens, invasive species, and transboundary pests poses unprecedented challenges to crop health and biosecurity on a global scale. Effective disease surveillance, timely recognition, and rapid reaction mechanisms are imperative to prevent spread of plant diseases, thereby safeguarding agricultural economies, trade networks, and rural livelihoods [8].

In addition to its agricultural and environmental significance, research in plant disease detection and classification holds promise for technological innovation and scientific advancement. Leveraging cutting-edge technologies such as artificial intelligence, ML, remote sensing, and genomic sequencing, researchers strive to develop sophisticated disease diagnosis tools, predictive models, and decision support systems for precision agriculture [9]. These technological innovations empower farmers with real-time insights, actionable intelligence, and data-driven solutions to effectively manage crop health, optimize resource utilization, and maximize agricultural productivity in an era of climate variability and resource constraints. In essence, the motivation for research in plant disease detection and classification transcends disciplinary boundaries, encompassing food security, environmental sustainability, economic resilience, and technological innovation [10]. By harnessing the collective efforts of scientists, policymakers, farmers, and stakeholders, we can address the complex challenges posed by plant diseases and pave the way for a more resilient, sustainable, and equitable agricultural future.

2. Literature Survey

In his proposal [11], Demilie advocated conducting comparison research that would evaluate the effectiveness of different methods for recognition and categorization of plant diseases. The results of their study provide insights into the efficacy of various strategies in this field, which assists researchers and practitioners in identifying appropriate ways for the control of plant diseases. In their review, Morchid et al. [12] focused on intelligent detection approaches for sustainable agriculture. These methods included Internet of Things (IoT)-based DL, and ML for the detection of plant diseases. The detailed evaluation that they conducted provides insightful information about the use of cutting-edge technology in agricultural settings. Sarah and her colleagues [13] investigated on the impact that super-resolution has on the automated diagnosis of plant diseases, with importance on detection of potato late blight. The research that they conducted emphasizes the use of sophisticated image processing methods to improve the accuracy of illness identification. Using IoT, ML, and DL, Prasad and Thyagaraju [14] presented a complete assessment of early plant disease diagnosis based on leaf analysis. Their research provides an overview of the extent to which these technologies have the potential to facilitate proactive disease management techniques. Hari et al. [15] suggested an enhanced federated DL system for the identification of diseases that affect plant leaves. In this work, they highlight recent developments in federated learning algorithms, which aim to improve the accuracy and scalability of illness detection models.

Utilizing deep features to achieve more precision, Reis, and Turk [16] presented an integrated DL and ensemble learning model for wheat disease diagnosis. When it comes to identifying illnesses that might impact wheat harvests, their approach offers some encouraging findings. To industrial farming systems, Sajitha et al. [17] carried out a review that focused on ML and DL image-based plant disease classification. The findings of this analysis provide valuable perceptions into extremely cutting-edge methods now available for the automated identification of diseases in agricultural settings. The authors Manoj and Sasilatha [18] suggested an automated technique for diagnosis of plant diseases that makes use of an effective deep ensemble learning mechanism. Through their study, they have shown breakthroughs in DL methods for the purpose of providing accurate and efficient disease diagnostics in smart agricultural applications. Vision transformers were the focus of Brown and De Silva's [19] proposal for a technology that might identify plant diseases using multispectral pictures. The determination of their research is to investigate the applications of transformer-based models in agricultural imaging with the purpose of improving disease detection. Using few-shot learning methods, Rezaei et al. [20] presented a method for the detection of plant diseases in situations with few data. The outcomes of their research suggest that few-shot learning was a viable method for tackling the constraints posed by data scarcity in disease detection efforts.

Within the context of greenhouse plant habitats, Wang, and Liu [21] suggested a technique for the identification of vegetable diseases by using an upgraded version of the YOLOv8 algorithm. The work that they do leads to the development of disease detection technologies that are both effective and scalable for greenhouse farming. To identifying and forecasting rice plant illnesses, Pahlawanto et al. [22] created an approach that makes use of CNN methods. The use of CNNs for the purpose of reliable disease identification in rice crops is the primary emphasis of their research. Using ML, Srinivas et al. [23] provided an improved framework for agricultural disease diagnosis, with an emphasis on accuracy and efficiency in disease identification. The purpose of their approach is to make it easier to implement timely interventions for disease control in agricultural systems. In their study, Trippa et al. [24] investigated the next-generation strategies. They highlighted creative ways for enhancing disease monitoring and management in agricultural settings. In their contribution to the development of automated disease diagnostic systems in agricultural operations, Lekha et al. [25] established a ML model for discovery of diseases that affect tomato leaf diseases.

To improving disease management tactics in rice production, Kulkarni, and Shastri [26] devised a method for the identification of rice leaf diseases by using ML techniques. The authors Rajaiah et al. [27] devised a technique for recognition of leaf diseases that makes usage of an ensemble classification approach in ML. Increasing the accuracy of illness diagnosis via the use of ensemble approaches is the primary emphasis of their work. By using CNNs and color space models, Nain et al. [28] were able to construct a system for the identification of plant diseases. The purpose of their research is to investigate whether CNNs are capable to properly diagnosing plant diseases based on color characteristics. Using a variety of convolutional neural network topologies, Banerjee and Mondal [29] presented an intelligent method for the identification of diseases that affect plant leaves. The work that they do helps to contribute to the development of reliable disease detection systems for precision agriculture. In their study, Singh et al. [30] improved precision agriculture by using CNN models to identify diseases that affect maize leaf tissue. The results of their research illustrate how CNNs may be used to improve the accuracy of disease recognition in maize growing crops.

By using bibliometric methods, Bonkra et al. [31] conducted an in-depth investigation on the trend of identifying apple leaf illnesses by ML. Through their research, they have provided valuable insights into the present level of disease detection in apple crops as well as future directions. In their study [32], Tewari and colleagues devised a technique for the automated identification of guava illness by using a variety of DL methodologies. As part of their research, they are concentrating on using DL approaches to diagnose diseases accurately and effectively in guava plants. At the same time as Pattanaik et al. [33] carried out an exploratory investigation of ML-enabled plant diseases evaluation, they highlighted the potential of artificial intelligence approaches in terms of enhancing disease management practices. As a contribution to the development of automated disease diagnostic systems in rice production, Kaur et al. [34] suggested a DL-based model for identification of biotic rice leaf disease conditions. Chelladurai and Sujatha [35] examined the use of image processing approaches that were based on thermal camera footage for the purpose of disease identification, namely in leaves. Through their research, they investigate the use of thermal imaging in agricultural settings for the purpose of accurately diagnosing diseases.

Using an ITSO-based neural network, Rajalakshmi et al. [36] were able to suggest a strategy for the identification of diseases that affect many crop species. The development of a disease detection system that is adaptable to multiple crop species is the primary focus of their scientific endeavor. The research conducted by Alam et al. [37] compared pre-trained models for the purpose of useful plant leaf disease detection. The results of their research contribute to the selection of appropriate models for a reliable disease diagnosis in plant leaves. To onion plant disease management, Kathole et al. [38] suggested an IoT-based smart agriculture method. This approach would include a variety of technologies for effective disease monitoring and control. When it came to the identification of non-visual maize diseases, Maginga et al. [39] applied wavelet transforms and hybrid CNN-LSTM models using data collected from IoT sensors. The research that they are doing investigates novel approaches to disease detection in maize crops by using sensor data. The authors Nobel et al. [40] offered a hybrid strategy for automated recognition of palm leaf diseases and the development of treatment. The authors placed an emphasis on the integration of new technologies for the purpose of successful disease management in palm crops.

3. Proposed System

Historically, farmers have depended on manual pest monitoring methods, sticky traps, and black light traps to identify and control pest infestations in their fields. However, the advent of DL technologies, particularly in the field of digital image processing, has ushered in transformative possibilities that surpass the capabilities of conventional methods. Researchers are increasingly focusing on leveraging DL to address the complex challenge of identifying plant diseases and pests, with the aim of revolutionizing agricultural practices.

Table 1 presents the detailed algorithm procedure of proposed plant disease detection and classification procedure. In Figure 1, DL, and specifically GPR-CNN is employed as a powerful tool for feature extraction and disease identification. Crop disease datasets undergo preprocessing and are then fed into the GPR-CNN model for feature extraction. Simultaneously, leaf images, another crucial element in understanding plant health, undergo similar preprocessing and testing through the GPR-CNN. The features extracted from the trained GPR-CNN model are then compared with the pre-existing features associated with various plant diseases. The comparison process involves assessing the loss computation and accuracy of the extracted features. This meticulous analysis is crucial for predicting and classifying the different plant diseases. The resulting comparison graph serves as a valuable visual representation, offering insights into the success of the GPR-CNN model in accurately identifying and categorizing plant diseases.

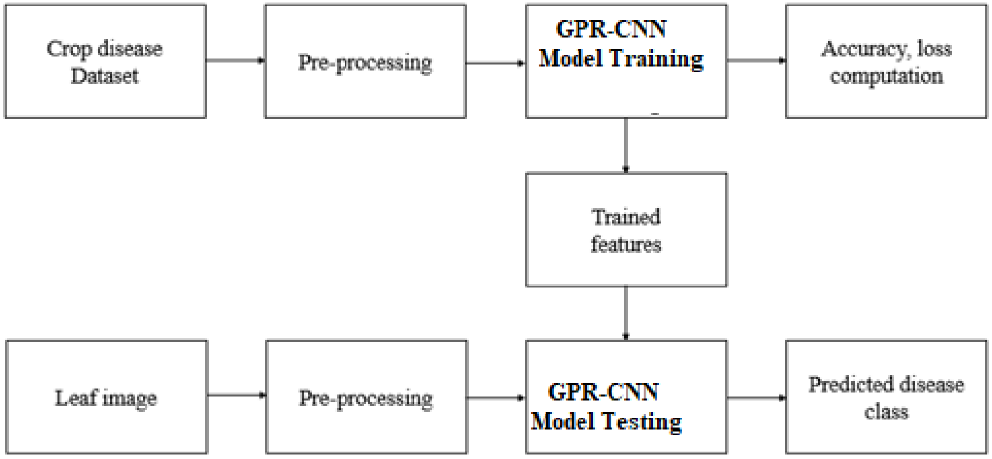

Fig. 1. Block diagram of proposed system.

Table 1. Proposed plant disease classification algorithm.

Step 1: Collect and preprocess crop disease datasets, ensuring uniformity and quality of images.

Step 2: Similarly, preprocess leaf images, preparing them for testing through the model.

Step 3: Employ GPR-CNN for feature extraction from both the crop disease datasets and leaf images.

Step 4: Train the GPR-CNN model using the preprocessed datasets, allowing it to learn and extract relevant features.

Step 5: Compare the features extracted by the trained GPR-CNN model with pre-existing features associated with various plant diseases.

Step 6: Perform loss computation and accuracy assessment of the extracted features to evaluate the effectiveness of the model.

Step 7: Utilize the comparison results to predict and classify different plant diseases based on the extracted features.

Step 8: Use the insights derived from the comparison graph to make proactive decisions regarding crop health management.

The integration of DL technologies into agriculture marks a paradigm shift in the way we approach crop health management. The ability of GPR-CNN to automatically learn and extract of plant diseases. Unlike traditional methods, which may rely on subjective visual inspections or limited datasets, DL empowers the agricultural community with data-driven insights for proactive decision-making. The implication of this research lies not only in the accurate identification of plant diseases but also in the potential to mitigate the impact of pests and insects on crop yields. By harnessing the power of DL, farmers can proactively address issues such as climate change-induced variations and unexpected pest levels, leading to more resilient and sustainable agricultural practices.

3.1 Crop disease dataset

The crop disease dataset comprises images representing various diseases and health states of plants, predominantly focusing on peppers, potatoes, and tomatoes. For Pepper Bell Bacterial Spot, the dataset contains a total of 997 images, with 797 images allocated for training and 200 for testing. Similarly, Pepper Bell Healthy comprises 1478 images, with 1182 used for training and 296 for testing. In the case of Potato Early Blight, there are 1000 images in total, with 800 designated for training and 200 for testing. Potato Healthy, on the other hand, consists of 152 images, with 122 utilized for training and 30 for testing. For Potato Late Blight, the dataset contains 1000 images, with 800 for training and 200 for testing.

Moving on to the tomato classes, Tomato Target Spot includes 1404 images, with 1124 for training and 280 for testing. Tomato Mosaic Virus comprises 373 images, with 298 used for training and 75 for testing. Tomato Yellow Leaf Curl Virus has the highest number of images in the dataset, totaling 3208, with 2566 for training and 642 for testing. Tomato Bacterial Spot includes 2127 images, with 1701 designated for training and 426 for testing. Similarly, Tomato Early Blight consists of 1000 images, with 800 for training and 200 for testing. Tomato Healthy comprises 1591 images, with 1273 used for training and 318 for testing. Tomato Late Blight includes 1909 images, with 1527 for training and 382 for testing. Tomato Leaf Mold has 952 images, with 761 for training and 191 for testing. Tomato Septoria Leaf Spot comprises 1771 images, with 1416 for training and 355 for testing. Lastly, Tomato Spider Mites Two-Spotted Spider Mite consists of 1676 images, with 1340 for training and 336 for testing. Finally, the dataset encompasses a total of 20638 images, with 16510 designated for training and 4128 for testing across all classes. Each class contributes to the diversity of the dataset, facilitating the development and evaluation of ML models for plant disease detection and classification.

3.2 Image pre-processing

Image preprocessing plays a crucial role in the pipeline of plant disease detection and classification systems, as it involves consistency, and compatibility of image data for subsequent analysis and model training. Each step in the preprocessing pipeline contributes to the overall efficacy and accuracy of the disease detection process, ensuring that the input images are appropriately formatted and standardized for machine learning algorithms. The first step in image preprocessing is reading the input images from the dataset. This involves loading the images from storage into memory using appropriate libraries or frameworks such as OpenCV, PIL (Python Imaging Library), or TensorFlow. Reading the images enables access to their pixel values, dimensions, and metadata, forming the foundation for subsequent preprocessing operations.

Once the images are read, resizing is often performed to ensure uniformity in size across the dataset. Resizing involves adjusting the dimensions of the images to a predefined resolution or aspect ratio, thereby standardizing their dimensions for consistency during model training and inference. This step is particularly crucial when working with deep learning models that require fixed input dimensions for processing. After resizing, the images are converted into numerical arrays, commonly referred to as image-to-array conversion. This process involves transforming the pixel values of the images into multidimensional arrays, where each element represents the intensity or color value of a specific pixel. By converting images to arrays, they can be efficiently processed and manipulated using numerical computation libraries such as NumPy or TensorFlow.

Subsequently, the image arrays are typically converted to floating-point format to facilitate numerical computations and enhance the precision of subsequent operations. Floating-point representation allows for more accurate representation of pixel values, particularly in cases where images contain high dynamic range or subtle variations in intensity. Normalization is another critical step in image preprocessing, aimed at standardizing the pixel values of the images to a common scale or range. Normalizing the images helps mitigate the effects of lighting variations, contrast differences, and pixel intensity disparities, ensuring that the input data are consistent and compatible for model training.

Indexing is often performed after preprocessing to associate each preprocessed image array with its corresponding label or class identifier. This indexing step facilitates data management, organization, and retrieval during model training and evaluation, enabling seamless integration with machine learning frameworks and libraries.Finally, the preprocessed image arrays can be saved to disk or storage for future use, enabling efficient data caching, archiving, and sharing. Saving the preprocessed arrays in a standardized format such as NumPy arrays or HDF5 files ensures data integrity, interoperability, and accessibility across different platforms and environments.

3.3 Proposed GA-PSO

The GA and PSO are evolutionary optimization algorithms that have found applications in feature extraction, particularly in the context of image processing and pattern recognition. Feature extraction involves selecting and transforming relevant features from raw data, aiming to enhance the discriminative power of the data for subsequent analysis, such as ML tasks. Table 2 shows the GA feature extraction algorithm. Table 3 shows the PSO feature extraction algorithm. The integration of GA and PSO involves combining their strengths to create a hybrid optimization algorithm. This hybridization aims to leverage the exploration and exploitation capabilities of both algorithms for more effective feature extraction. In this context, the chromosome or particle represents a feature subset, and the optimization process evolves these subsets for improved discrimination in the dataset. The algorithm iterates through the GA and PSO steps, allowing for complementary exploration and exploitation of the solution space. The advantages of this hybrid approach lie in its ability to find optimal or near-optimal feature subsets, considering the global search capabilities of PSO and the evolutionary search capabilities of GA. The combination of these algorithms enhances the efficiency and effectiveness of feature extraction, contributing to the overall performance of subsequent ML models trained on the processed data.

3.4 Proposed GPR-CNN

CNNs have emerged as a cornerstone technology in the domain of image processing and computer vision, revolutionizing the landscape of various applications ranging from object detection to medical imaging. In plant disease detection and classification, the adoption of CNNs has been instrumental in addressing the inherent complexities and challenges associated with analyzing large-scale image datasets containing intricate patterns and subtle variations indicative of disease symptoms. The need for CNNs in this domain stems from several key factors, each underscoring the unique capabilities and advantages offered by this deep learning architecture.

Table 2. GA Feature Extraction Algorithm.

Step 1: Chromosome Representation: In GA-based feature extraction, each solution or individual is represented as a chromosome. The chromosome comprises a set of genes, where each gene corresponds to a specific feature or attribute in the dataset. **Step 2: Initialization:** An initial population of chromosomes is randomly generated. Each chromosome represents a potential subset of features.

Step 3: Fitness Evaluation: The fitness of each chromosome is evaluated based on a fitness function that quantifies how well the corresponding subset of features discriminates between different classes or categories in the data.

Step 4: Selection: Chromosomes are selected for reproduction based on their fitness. The more fit chromosomes are more likely to be selected, mimicking the principle of natural selection.

Step 5: Crossover: Pairs of selected chromosomes undergo crossover (also known as recombination) to create new offspring. This emulates the genetic crossover process, combining features from both parents to produce potentially more effective subsets.

Step 6: Mutation: Random changes, or mutations, are introduced in the offspring's genes, allowing for exploration of new feature combinations.

Step 7: Replacement: The new offspring replaces fewer fit individuals in the population, ensuring that the overall population evolves toward more optimal feature subsets.

Step 8: Termination: The process stops after reaching best fitness.

Table 3. PSO Feature Extraction

Step 1: Particle Representation: PSO involves a population of particles, where each particle represents a potential solution (feature subset). The position of each particle corresponds to a point in the solution space.

Step 2: Initialization: Particles are randomly initialized in the solution space, and each particle is associated with a velocity indicating the direction and magnitude of its movement.

Step 3: Fitness Evaluation: The fitness of each particle is assessed based on a fitness function, like GA. It measures how well the corresponding feature subset performs in discriminating between classes.

Step 4: Velocity Update: The current velocity of each particle, as well as its personal best position (the individual's historical best) and the global best position (the best position among all particles in the population) are taken into consideration while updating the velocity of each particle.

Step 5: Position Update: Using the particle's present position and its updated velocity, the position of each particle is updated, which allows for the determination of the particle's new location inside the solution space.

Step 6: Best Position Update: The personal best and global best positions are updated if a particle discovers a better solution during its movement.

Step 7: Termination: The process continues for multiple iterations, and termination occurs when a predefined criterion is met.

First and foremost, CNNs are well-suited for extracting hierarchical features from image data, thereby enabling robust and discriminative representation learning. Unlike traditional machine learning algorithms that rely on handcrafted feature engineering, CNNs leverage learnable filters and convolutional layers to automatically learn and extract relevant features directly from raw pixel intensities. Furthermore, CNNs exhibit translational invariance, enabling them to recognize patterns and features across different spatial locations within an image. This property is particularly advantageous in plant disease detection scenarios where the exact location and orientation of disease symptoms may vary across different instances of the same disease. By leveraging convolutional operations and pooling layers, CNNs can effectively capture spatial relationships and spatial hierarchies in the input data, facilitating robust and invariant feature representation across diverse image samples.

Moreover, CNNs are capable of learning hierarchical representations of increasing complexity through multiple layers of abstraction, thereby facilitating the development of deep architectures capable of modeling intricate relationships within the data. Deep CNN architectures have demonstrated superior performance in capturing complex patterns and discriminating between fine-grained categories, making them well-suited for tasks such as fine-grained plant disease classification and localization.

Additionally, CNNs can leverage transfer learning, a powerful technique that enables the transfer of knowledge and representations learned from one task or dataset to another related task or dataset. Pretrained CNN models serve as feature extractors or initialization points for training specialized plant disease detection models with limited annotated data. By fine-tuning pretrained CNNs on plant disease datasets, researchers can expedite model convergence, improve generalization performance, and alleviate the need for large amounts of labeled training data.

This neural network architecture, characterized by a thoughtful integration of convolutional and fully connected layers, represents a robust framework for crop disease recognition. The convolutional layers excel in capturing spatial hierarchies and relevant patterns, while the fully connected layers leverage these learned features to make informed predictions. The hierarchical nature of the architecture allows the model to learn and represent features at different levels of abstraction, providing a nuanced understanding of the input data. The challenges in designing such architectures lie in striking a balance between model complexity and efficiency. The problem of too many parameters, often encountered in fully connected feedforward networks, is mitigated through the parameter sharing mechanism inherent in convolutional neural networks. This mechanism ensures that the same set of parameters is utilized across multiple functions of the model, significantly reducing the risk of overfitting, and enhancing training efficiency. The convolutional operation's ability to achieve local invariance addresses the issue of image stability, ensuring that the model can effectively handle variations in scaling, translation, and rotation common in real-world agricultural images.

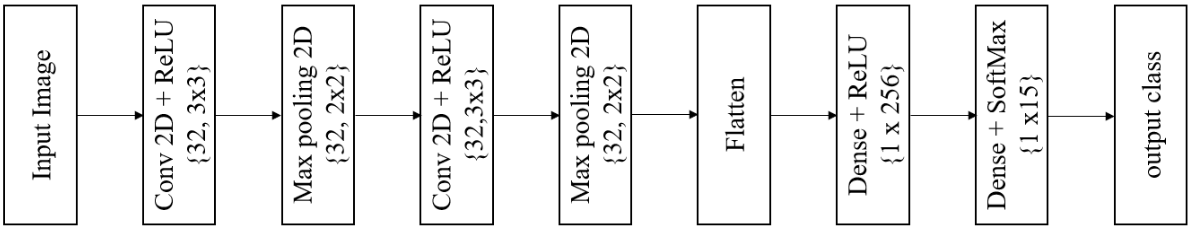

Fig. 2. Proposed GPR-CNN.

The architecture of a neural network plays a pivotal role in determining its ability to effectively address complex tasks, and in the realm of image-based tasks like crop disease recognition, a well-designed architecture is of paramount importance. Figure 2 outlines the layers of the proposed neural network for crop disease recognition, shedding light on the intricate details such as the number of filters, kernel sizes, and resulting feature sizes. This elaborate architecture incorporates convolutional and fully connected layers, each serving a distinct purpose in the hierarchical process of feature extraction, abstraction, and classification. The first layer, Conv 2D + ReLU, initiates the feature extraction process. With 32 filters and a 3 x 3 kernel size, this convolutional layer convolves the input image, capturing essential patterns that may indicate the presence of diseases in crops. The resulting feature size of 62 x 62 x 32 indicates the extraction of 32 features from the input image.

Following the feature extraction, the Max Pooling 2D layer with a 3 x 3 kernel size is employed to reduce the spatial dimensions of the feature map, enhancing computational efficiency, and promoting translational invariance. The feature size diminishes to 31 x 31 x 32, reflecting the down-sampling achieved through the max pooling operation. This reduction in dimensionality helps in focusing on the most salient features, facilitating a more compact and meaningful representation of the data. The network then undergoes a second round of feature extraction with another Conv 2D + ReLU layer. This layer, again with 32 filters and a 3 x 3 kernel size, refines the features learned in the initial convolutional layer. The feature size further reduces to 29 x 29 x 32, reflecting the network's ability to distill intricate details from the input image. This hierarchical feature extraction is crucial for capturing both low-level and high-level patterns that are indicative of various crop diseases. A subsequent Max Pooling 2D layer follows, maintaining the stride of 3 x 3 for further downsampling. The feature size now stands at 14 x 14 x 32, demonstrating the continued reduction in spatial dimensions. This pooling operation aids in abstracting high-level features while also contributing to the network's ability to generalize across diverse images, a crucial characteristic for robust crop disease recognition.

The Flatten layer then transforms the 3D feature map into a 1D vector, preparing the data for input into the fully connected layers. With a feature size of 1 x 6272, this layer ensures a seamless transition from the convolutional layers to the densely connected layers. The flattened vector retains the learned features in a structured format, facilitating the subsequent processing stages. Moving into the fully connected layers, the Dense + ReLU layer with 256 neurons introduces non-linearity once again, allowing the network to capture intricate relationships between the learned features. The ReLU activation function enhances the model's ability to learn complex representations of the flattened input. The feature size at this stage is 1 x 256, indicating the condensed yet rich representation of high-level features.

The final layer, Dense + SoftMax, acts as the output layer with 15 neurons, each corresponding to one of the possible crop diseases. The SoftMax activation function is applied, converting the raw output into probabilities. This layer provides a probabilistic distribution over the different disease classes, enabling the model to categorize the input image based on the highest probability. The feature size of 1 x 15 represents the output classes, and the network is trained to assign high probabilities to the correct class, facilitating accurate disease identification.

4. Results and Discussions

In this comparative analysis, diverse methodologies for plant disease detection and classification are evaluated using consistent plant disease datasets. The study assesses the efficacy of different techniques based on performance metrics providing insights into the strengths and limitations of each approach. By benchmarking multiple methods on the same datasets, researchers aim to identify optimal strategies for accurate and reliable plant disease diagnosis, facilitating advancements in agricultural technology and crop management practices.

4.1 Prediction Results

Figure 3 shows the predicted outcome with various pesticides suggested. The management of plant diseases in agricultural crops requires an integrated approach that combines cultural practices, crop rotation, disease-resistant varieties, and judicious use of pesticides. It is essential for farmers to adopt sustainable and environmentally friendly pest management practices to ensure the long-term health and productivity of their crops, while also minimizing the risks associated with pesticide use to human health and the environment. Regular monitoring, early detection, and timely intervention are key components of successful disease management strategies in agriculture.

Pepper Bell - Bacterial Spot: Bacterial spot is a common disease affecting pepper plants, caused by various species of bacteria. To manage bacterial spot in pepper plants, farmers can use copper-based fungicides. Copper compounds such as copper oxychloride or copper hydroxide are effective in controlling bacterial infections. These fungicides work by inhibiting bacterial growth and preventing the spread of the disease on pepper foliage. Farmers should apply copper-based fungicides according to label instructions and adhere to recommended application rates to ensure effective disease control while minimizing the risk of phytotoxicity.

Potato - Early Blight: Early blight is a fungal disease that affects potato plants, caused by the fungus Alternaria solani. To manage early blight in potato crops, farmers can use fungicides containing active ingredients such as chlorothalonil or mancozeb. These fungicides act by inhibiting fungal spore germination and growth, thereby reducing disease severity. Farmers should apply fungicides preventively or at the first signs of disease development and adhere to proper application timings and rates to achieve optimal disease control.

Potato - Late Blight: Late blight is a devastating fungal disease affecting potato plants, caused by the oomycete pathogen Phytophthora infestans. To manage late blight in potato crops, farmers can use fungicides containing active ingredients such as chlorothalonil, mancozeb, or metalaxyl. These fungicides work by suppressing fungal growth and reducing spore production, thus limiting the spread of the disease within potato fields. Farmers should apply fungicides preventively and adhere to recommended application schedules to effectively control late blight and minimize yield losses.

Tomato - Target Spot: Target spot, also known as early blight, is a fungal disease affecting tomato plants, caused by the fungus Corynespora cassiicola. To manage target spot disease in tomato crops, farmers can use fungicides containing active ingredients such as chlorothalonil, azoxystrobin, or copper compounds. These fungicides help inhibit fungal growth and reduce the severity of target spot symptoms on tomato foliage. Farmers should apply fungicides preventively or at the first signs of disease onset, ensuring thorough coverage of tomato plants to achieve optimal disease control.

Tomato - Tomato Yellow Leaf Curl Virus (TYLCV): Tomato yellow leaf curl virus (TYLCV) is a viral disease transmitted by the silverleaf whitefly (Bemisia tabaci) and affects tomato plants worldwide. Unfortunately, there are no chemical treatments available to control viral diseases like TYLCV. Instead, farmers should focus on implementing integrated pest management (IPM) strategies to manage whitefly populations and reduce virus transmission. IPM practices may include the use of insecticidal soaps, neem-based products, reflective mulches, and physical barriers to deter whiteflies and minimize virus spread. Additionally, farmers should plant disease-resistant tomato varieties and practice strict sanitation measures to minimize virus inoculum sources and disease incidence in tomato fields.

4.2 CNN Results

In Figure 4, a detailed depiction of the relationship between epochs or iterations and performance metrics such as accuracy and loss is presented. The y-axis illustrates the values of accuracy and loss, while the x-axis represents the progression of epochs or iterations during the training process. Notably, the green line corresponds to the accuracy metric, reflecting the model's predictive performance, while the blue line signifies the loss metric, indicating the magnitude of error between predicted and actual values.

```
Crop Disease Recognize as : Potato___healthy
Suggested pesticide is : No Pesticide is required

Crop Disease Recognize as : Potato___Early_blight
Suggested pesticide is : Proxanil

Crop Disease Recognize as : Potato___Early_blight
Suggested pesticide is : Proxanil

Crop Disease Recognize as : Tomato_Bacterial_spot
Suggested pesticide is : Insecticidial Soap and Horticultural Oil

Crop Disease Recognize as : Tomato_Bacterial_spot
Suggested pesticide is : Insecticidial Soap and Horticultural Oil

Crop Disease Recognize as : Tomato_Leaf_Mold
Suggested pesticide is : Applying fungicides
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Fig. 3. Predicted outcomes with pesticide suggestions.

With each successive epoch or iteration, observable trends emerge, revealing a progressive improvement in accuracy and a simultaneous reduction in loss. This phenomenon is indicative of the iterative nature of model training, wherein the algorithm iteratively adjusts its parameters to minimize prediction errors and enhance predictive accuracy. As the model undergoes multiple iterations, it refines its internal representations and learns to capture intricate patterns and relationships within the data, leading to incremental improvements in performance.

At epoch 10, a critical juncture in the training process, the effects of iterative optimization become particularly pronounced. The accuracy curve exhibits a steady upward trajectory, signifying an enhancement in the model's ability to correctly classify instances within the dataset. Concurrently, the loss curve demonstrates a consistent downward trend, indicating a reduction in prediction errors and an improved fit between the model's predictions and the ground truth labels. These observations underscore the efficacy of the training regimen in progressively refining the model's predictive capabilities over multiple epochs.

Furthermore, the convergence of the accuracy and loss curves at epoch 10 suggests that the model is approaching an optimal state of performance, wherein further iterations may yield diminishing returns in terms of accuracy improvement or loss reduction. This convergence phenomenon signifies a balance between model complexity and generalization, wherein the model achieves high accuracy on the training data while minimizing overfitting to noise or spurious patterns.

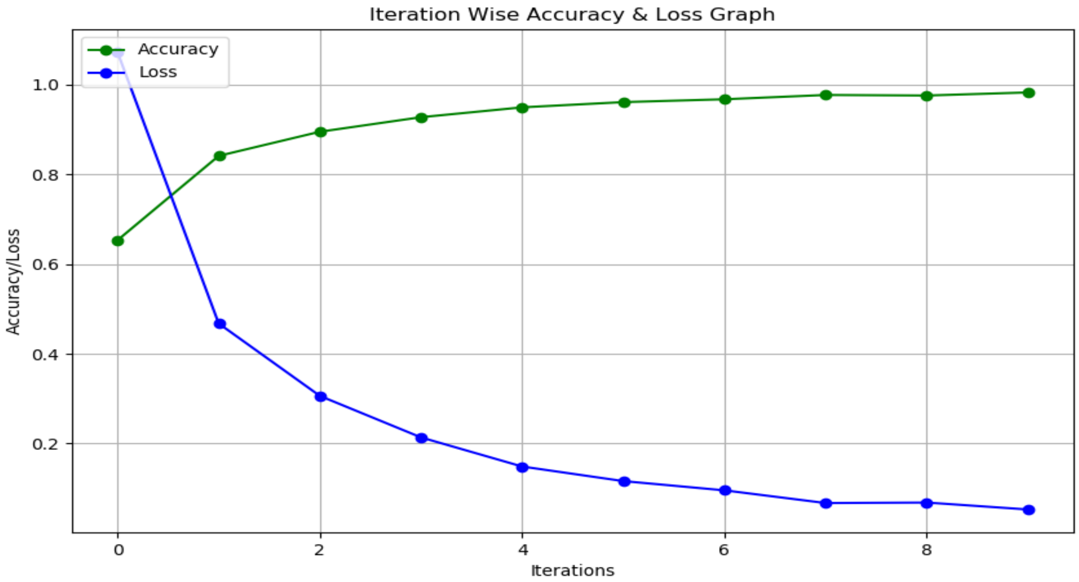

Fig. 4. Iteration wise accuracy & loss graph.

4.3 ResNet Results

Table 4 and Figure 5 provides a comprehensive performance comparison between the proposed method and existing techniques, including Naive Bayes Classifier (NBC), Random Forest Classifier (RFC), and Support Vector Machine (SVM). The evaluation metrics considered are accuracy, precision, recall, and F1-score, providing a nuanced understanding of the effectiveness of each method in plant disease detection and classification. In terms of accuracy, the proposed method outshines all existing techniques, achieving an impressive 99.173%. This indicates the model's exceptional capability to correctly identify and classify plant diseases. Precision, a measure of the model's ability to avoid false positives, is similarly elevated in the proposed method at 99.103%, surpassing existing methods. Recall, which gauges the model's ability to capture true positives, is notably high for the proposed method at 98.29%, demonstrating its proficiency in identifying diseased plants.

The F1-score, a harmonic mean of precision and recall, further accentuates the superiority of the proposed method, reaching 99.136%. This balanced metric indicates that the proposed model not only excels in minimizing false positives and false negatives but achieves an optimal trade-off between precision and recall. Comparatively, existing methods such as NBC, RFC, and SVM demonstrate respectable performance, with SVM exhibiting the highest accuracy among them at 94.783%. However, the proposed method significantly surpasses these benchmarks, emphasizing its potential as an advanced and highly accurate tool for plant disease detection and classification. These results underscore the efficacy of the proposed DL-based approach in enhancing the precision, recall, and overall accuracy of plant disease detection when compared to traditional ML methods. The proposed method's superior performance across multiple metrics suggests its potential for transformative impact in agricultural practices, offering a robust and reliable solution for combating plant diseases.

Table 4. Performance comparison.

Method	Existing NBC	Existing RFC	Existing SVM	Proposed Method
Accuracy (%)	89.37	90.33	94.783	99.173
Precision (%)	88.381	92.483	94.283	99.103
Recall (%)	89.193	90.183	93.83	98.29
F1-Score (%)	90.384	93.48	96.182	99.136

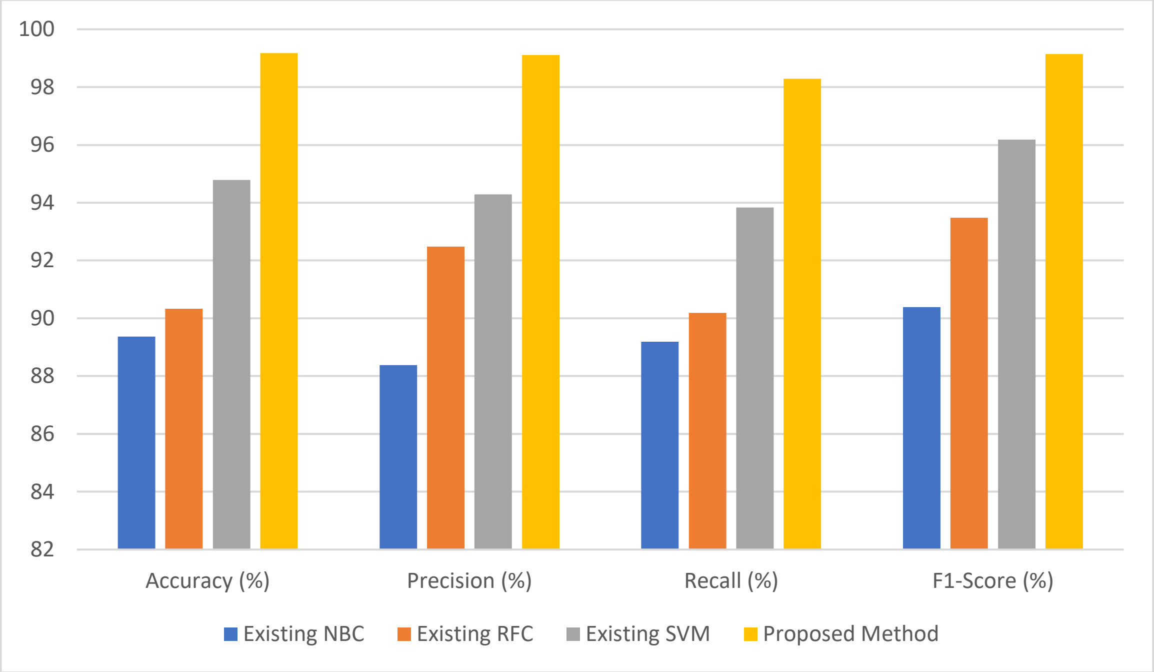

Figure 5. Graphical representation of performance.

5. Conclusion

In conclusion, our research endeavors to bridge the gap between traditional agricultural practices and cutting-edge technology by introducing a sophisticated solution for plant disease detection and pesticide suggestion. The agricultural sector, as a linchpin for a nation's growth, demands innovative approaches to address the critical challenges posed by plant diseases. The limitations of subjective visual inspections and resource-intensive conventional methods prompted the integration of ML and DL techniques, leading to the development of the Proposed model. The experimentally evaluated software solution showcased the efficacy of the GPR-CNN-based architecture in robust feature extraction and accurate disease classification. The preprocessing step further refined the model's performance by eliminating various types of noise, ensuring the normalization of dataset images. The commendable accuracy rates achieved in plant leaf disease detection validate the potential of our proposed model to revolutionize the identification and management of plant diseases in agriculture. Taking a step beyond disease detection, our research extends the model's capabilities to include pesticide suggestion. This novel integration aims to provide farmers and agriculture professionals with a holistic solution for disease management. By leveraging the learned features of the DL architecture, the model delivers precise and tailored pesticide recommendations based on the specific disease identified. This comprehensive approach not only identifies plant diseases but also empowers stakeholders with actionable insights for targeted interventions. The potential impact of our research on agricultural practices is substantial. The seamless integration of plant disease detection and pesticide suggestion into a unified framework aligns with the evolving needs of modern agriculture. This innovative approach promises to enhance the efficiency, accuracy, and sustainability of agricultural processes, contributing to increased crop yields and reduced economic losses. As we move forward, further research and development can explore the scalability and adaptability of the Proposed model across diverse agricultural contexts. Continuous refinement and expansion of the dataset can improve the model's generalization capabilities and ensure its applicability to a wide range of crops and regions. Additionally, collaboration with industry stakeholders and policymakers is essential to facilitate the integration of this technology into real-world agricultural practices.

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