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Shift Invariant for Identification of Plant Diseases

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Abstract
The backbone of civilization is agriculture. The main difficulty in agriculture is keeping plants from contracting diseases from their natural enemies and pest insects. One way to determine if a plant has a specific illness is with the use of CNN (Convolution Neural Network), also known as the Shift Invariant (SI) algorithm. The SI technique is a type of artificial neural network that is used in image recognition and is specifically designed to process picture pixels as input. The creation of automatic screening technologies is based on this kind of application. These tools could lead to more secure food production and sustainable agriculture techniques. The goal of these studies is to automatically identify crop illnesses so that we can protect the plants.

I. Introduction

It has long been a tradition to produce food through agriculture. Throughout the world, it is acrucial source of income for people. Animals that depend on plants for food, oxygen, and othernecessities are likewise dependent on them, making plants essential not just for people. Toincrease food production, the government and specialists are making substantial efforts, andthese efforts are showing results in the actual world. All living things in the ecosystem areimpacted in some manner when a plant contracts a disease. Each part of the plant, includingthe root, stem, leaf, and branch, might be impacted by this disease. Even the ailments that affectplants, including bacterial and fungal disorders, can vary. The disease that affects the crops willdepend on variables like the climate. There are a lot of people that struggle with food insecurity.This happens as a result of inadequate food crop production. Even substantial climate changeswill affect how plants develop. Natural disasters of this kind are unavoidable.

Early plantdisease detection aids in preventing Severe and significant crop losses. The proper insecticidesmust be used by farmers on their crops. Crops and fields suffer when there are too manypesticides used. Seeking professional counsel can assist you in avoiding chemical overuse onplants. For the benefit of farmers and other agricultural professionals, numerous studies havefocused on plants. An illness can easily be identifying if it is evident to the unaided eye. If thefarmer is equipped with knowledge and keep an eye on the crops on a regular basis, the ailmentmight be identified and treated early. This stage, though, is only present when the disease issevere or crop production is inadequate. There are also various innovations. The developmentof automated disease detection techniques is advantageous to farmers.

This method produces results that are appropriate for micro-, small-, and large- scaleagricultural cultivation. An important aspect of the outcomes is that the abnormalities arequickly identified, and the results are precise.Deep shift Invariant or Convolutional Neural Network is utilized in this study to identify infected and healthy leaves, as well as to detect illness in afflicted plants. The CNN or SI model is designed to suit both healthy and sick leaves; photos are used to train the model, and the output is determined by the input leaf.

It helps to meet the needs of the growing population. However, the use of such materials is not harmful to the environment. Applying thistype of negatively impacts biodiversity, that including Animals (Birds, Insects and Fish etc.,), Populations (air pollution, water pollution etc.,), as well as water, soil, and air quality. Their also constitutes a risk to human health, with both chronic and acute effects.While protecting harvests we limit the usage of pesticides. Indeed, the farmers to make proper practices in the right place and at the right time. However, assessing the growth line of fields is not simple, and it requires a very high level of expertise. Indeed, a disease can be spread from one plant species to another, or even from one variety to another variety.

Assessing the plant healthiness of plots is also time consuming. In large farms it can’t possible to checking the condition of every plant. Difficulty accessing certain crops complicates prospecting. The SI or CNN automatic identification tool support us to find diseases by imagery has the potential to solve all these issues by using automatic prospection or expert assistance tools.Determining plant health through an imageis, however, it is very difficult task to maintain crops are rich and complex environments. Their evolution is constant, with flowers, leaves, vegetable, and fruits Changes throughout the season.

Their appearance also changes slightly during the day, as the amount and angle of solar radiation affect their spectral response. Several techniques or tools have been used to develop identification method for crop diseases, whether real conditions or under controlled. These SI or CNN technique were based in particular on the analysis of near-infrared reflectance andvisible, on the development of vegetation indexes or by pattern analysis.Some of these issues are operational in nature and relate to weather constraints,image acquisition,availability,deployment costs, real-time diagnostic capabilities andprocessing speed. Analysing images from the fields adds other issues, such as the ability to process complex elements like non-uniform backgrounds or foliage. Other disturbances are linked to the complexity of phytosanitary problems, such as symptom variability over time and between species, or the potential for multiple disorders to appear simultaneously. Techniques capable of overcoming these challenges require the development of functional automated disease identification solutions.Here, we demonstrate the technical feasibility using a CNN or SI approach utilizing 54,306 images of 14 crop species with 26 diseases (or healthy) made openly available through the project PlantVillage. An example of each crop—disease pair can be seen in **Figure 1**

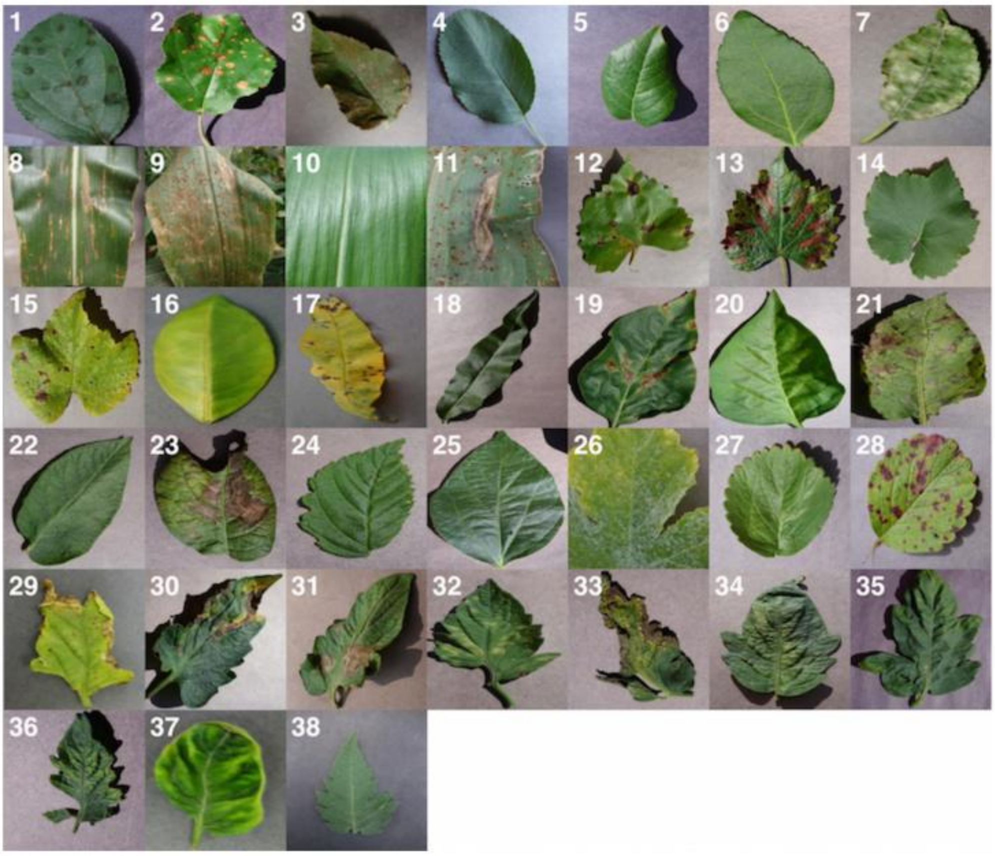

FIGURE 1 | Example of leaf images from the PlantVillage dataset, representing every crop-disease pair used. **(1)** Apple Scab, *Venturia inaequalis* **(2)** Apple Black Rot, *Botryosphaeria obtusa* **(3)** Apple Cedar Rust, *Gymnosporangium juniperi-virginianae* **(4)** Apple healthy **(5)** Blueberry healthy **(6)** Cherry healthy **(7)** Cherry Powdery Mildew, *Podoshaera clandestine* **(8)** Corn Gray Leaf Spot, *Cercospora zeae-maydis* **(9)** Corn Common Rust, *Puccinia sorghi* **(10)** Corn healthy **(11)** Corn Northern Leaf Blight, *Exserohilum turcicum* **(12)** Grape Black Rot, *Guignardia bidwellii*, **(13)** Grape Black Measles (Esca), *Phaeomoniella aleophilum, Phaeomoniella chlamydospora* **(14)** Grape Healthy **(15)** Grape Leaf Blight, *Pseudocercospora vitis* **(16)** Orange Huanglongbing (Citrus Greening), *Candidatus Liberibacter spp.* **(17)** Peach Bacterial Spot, *Xanthomonas campestris* **(18)** Peach healthy **(19)** Bell Pepper Bacterial Spot, *Xanthomonas campestris* **(20)** Bell Pepper healthy **(21)** Potato Early Blight, *Alternaria solani* **(22)** Potato healthy **(23)** Potato Late Blight, *Phytophthora infestans* **(24)** Raspberry healthy **(25)** Soybean healthy **(26)** Squash Powdery Mildew, *Erysiphe cichoracearum* **(27)** Strawberry Healthy **(28)** Strawberry Leaf Scorch, *Diplocarpon earlianum* **(29)** Tomato Bacterial Spot, *Xanthomonas campestris pv. vesicatoria* **(30)** Tomato Early Blight, *Alternaria solani* **(31)** Tomato Late Blight, *Phytophthora infestans* **(32)** Tomato Leaf Mold, *Passalora fulva* **(33)** Tomato Septoria Leaf Spot, *Septoria lycopersici* **(34)** Tomato Two Spotted Spider Mite, *Tetranychus urticae* **(35)** Tomato Target Spot, *Corynespora cassiicola* **(36)** Tomato Mosaic Virus **(37)** Tomato Yellow Leaf Curl Virus **(38)** Tomato healthy.

II. Materials and Methods

A generalized overview of the identification of plant diseases using CNN or SI is presented in**Figure 2**. To implement our proposed work, firstly, the images of diseased leaves of corn, tomato, and potato are collected from the Corn and PlantVillage dataset as well as from the field. Then the images are labelled according to the disease classes based on expert knowledge in case of field images. After that, pre-processing of images is performed which includes resizing of images, filtering of images, and different data augmentation techniques such as flipping, rotation, shifting and whitening to increase the dataset size. The training, and the testing images are fed into the CNN or SI model and the features are extracted. At last, we have used two different machine learning classifiers to classify the diseased leaf images. A detailed description of this implemented models is discussed in subsequent sub-sections.

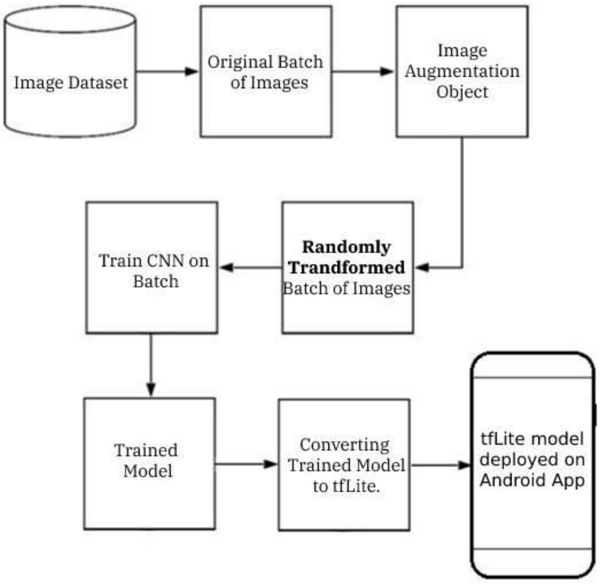

FIGURE 2 | Block Diagram of Proposed System

(1) The first step is to collect data. We are using the PlantVillage Dataset, which is widely available.
(2) Augmentation and Pre-processing of the collected dataset is done using pre-processing and Image-data generator API by Keras.
(3) Building SI(Shift Invariant) or CNN(Convolutional Neural Network) Model (Vgg-19 architecture) for classification of various plant diseases.
(4) With the help of TensorFlow lite, Developed model will be deployed on the Android Application.

III. SHIFT INVARIANT ORCONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

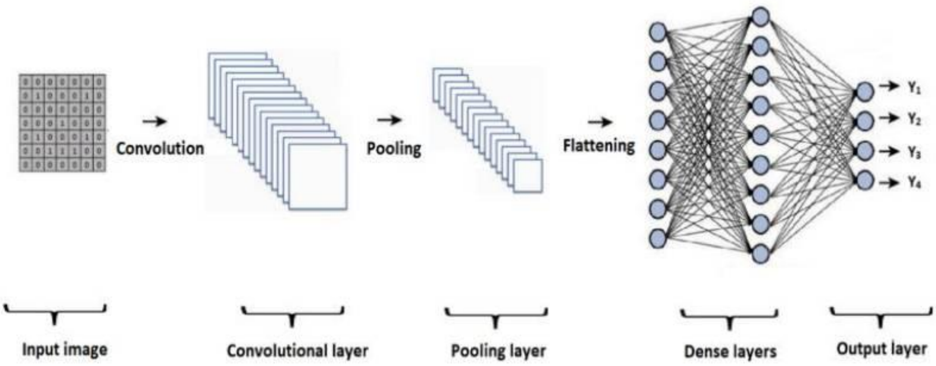

FIGURE 3 | SI or CNN Architecture

A SI or CNN has three layers: a Convolutional layer, a pooling layer, and a fully connected layer in Figure 3.

3.1 Convolutional layer

This Layer, produces an activation map by scanning the pictures several pixels at a time using a filter.

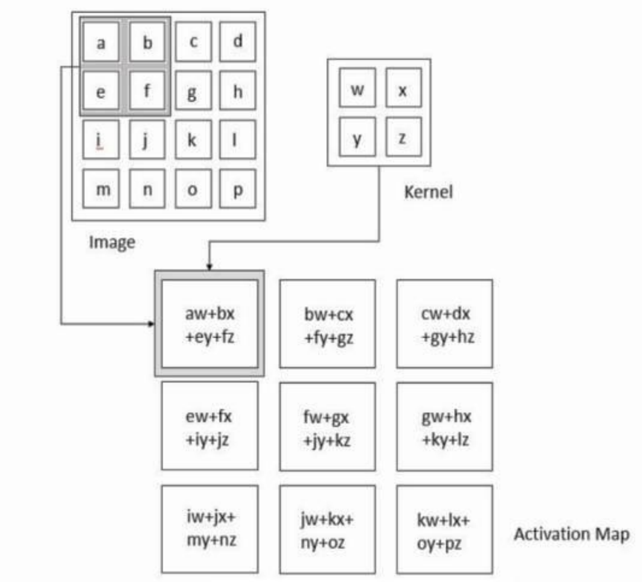

FIGURE 4 | Convolution Layer

3.2 Pooling Layer

This layer used to, reduces the amount of data created by the convolutional layer so that it is stored more efficiently. Figure 5 shows the internal working of the pooling layer

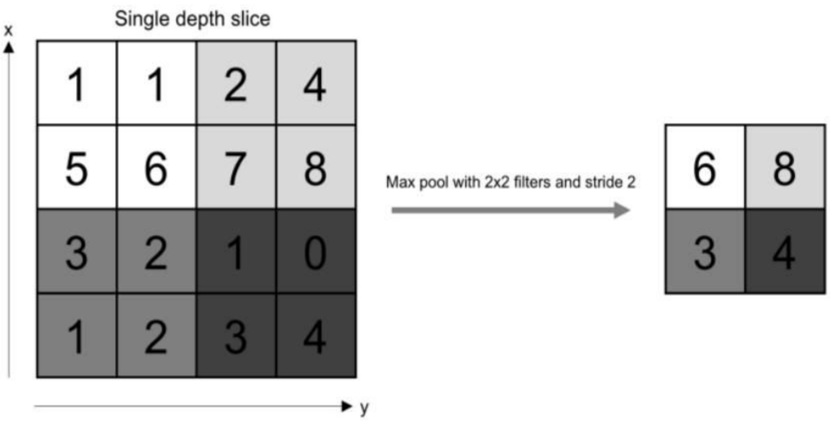

FIGURE 5 | Pooling Layer

3.3 Fully Connected Layer

Fully connected input layer – The preceding layer's output is "flattened" and turned into a single vector which is used as an input for the next stage.

The first fully connected layer – adds weights to the inputs from the feature analysis to anticipate the proper label.

Fully connected output layer – offers the probability for each label in the end.

Figure 6 shows the internal working of fully connected layer

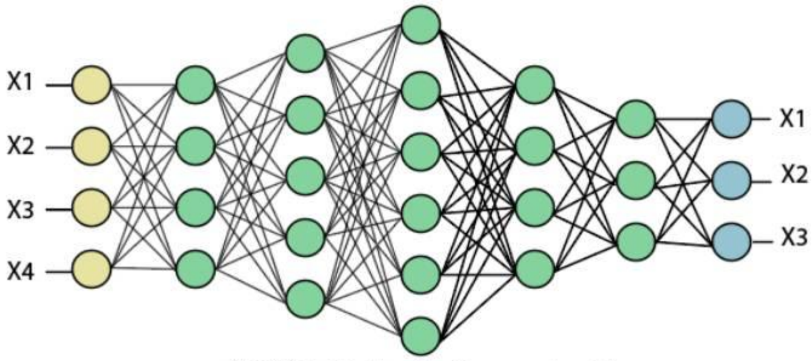

FIGURE 6 | Fully Connected Layer

IV. RESULT

A 95.6% accuracy rate was achieved using early stopping while training the model on 50 epochs. Figure 7 depicts the visualization of training and validation accuracy.

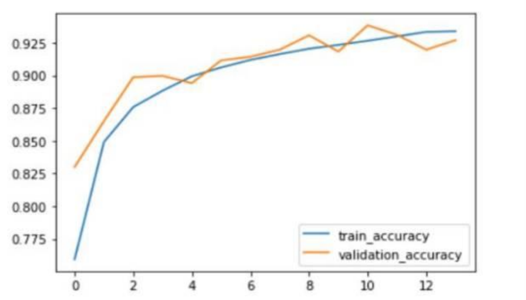

FIGURE 7 | Training vs Validation

V. CONCLUSION & FUTURE WORK

We are successful in creating disease classification techniques used for plant leaf disease detection. A deep learning model that can be used for automatic detection and classification of plant leaf diseases is created. Tomato, strawberry, soybean, raspberry, potato, corn, Pepper bell, peach, orange, grape, cherry, blueberry, apple are 13 species on which the proposed model is tested. 38 classes of plants were taken for identification through this work. We were successfully able to work with the image data generator API by Keras. Through this, we were able to do image-processing tasks. We were also able to create the vgg-19 model which is an advanced convolution model and train the model with the data for prediction. The prediction is done by our model is almost correct. We have successfully deployed these models on the android app and are trying to increase the accuracy of the android app as well as the model.

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