

Application of deep learning models for pest detection and identification

Ayesha Rafique ^{a,*}, Rabia Noor Enam ^a, Madiha Abbasi ^a, Noreen Akram ^a

^a Sir Syed University of Engineering and Technology, Karachi, Pakistan

* Corresponding author: Ayesha Rafique, Email: arafique@ssuet.edu.pk

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ABSTRACT

The quality and productivity of crops are seriously threatened by insect infestations, which is the primary focus of this research. Traditional monitoring methodologies tend to be ineffective and incorrect, resulting in wasted resources and loss of money. By incorporating cutting-edge AI and deep learning technologies, this study unveils a fresh method for rapid and precisely identifying pests in agricultural settings. This research makes use of high-resolution image technologies and Convolutional Neural Networks (CNNs) to showcase the promise of deep learning models in automated pest detection. The generalizability and model performance may be improved using transfer learning techniques leading to more efficient use of available resources. Key goals of this research include extensive testing across varied pest types and environmental settings, combined with the design and refinement of a CNN model specifically engineered for accurate pest identification. The gap between traditional pest monitoring practices and data-driven procedures is filled by the suggested method which ensures a significant increase in agricultural productivity that will contribute to greater food security and overall economic prosperity. This research strengthens the influential effects on agriculture, including enhancement of pest control, increasing food security, and boosting economic expansion. To promote this cutting-edge use of deep learning in agriculture, continuous cooperation between academics, businesses, and farmers is essential.

1. Introduction

Agriculture is crucial for all the sustaining economies and ensures that people can access nutritious food. Pest infestations are a significant problem that is threatening agricultural production and quality. These difficulties are not trivial for such an important business as ineffective resource allocation and monetary losses have been done from using time-consuming, labour-intensive, and inaccurate approaches for monitoring pests. Recent breakthroughs in artificial intelligence and deep learning have reshaped the way to approach pest detection to tackle pest identification in agriculture, offering much faster, more accurate and reliable alternatives to traditional manual methods. This study

focuses on applying deep learning methods and techniques to improve how the pests are identified in agricultural environments aiming to make the process more precise and efficient.

One of the reasons that deep learning models have become powerful tools for automated pest identification is the availability of various datasets and the advancement in complications of high-resolution imaging technology [1]. These models use Convolutional Neural Networks (CNN) which are capable to analyse complex visual patterns and time series, making it highly reliable for the detection of pests and classification of healthy crops. One important technique used here is transfer learning which helps us using models to execute better originally trained on similar tasks. This is to intensify

model's capability and their generalizability to use on different kinds of crops and crop pests.[2]

The primary objective of this research is to create and test deep learning-based models for automated pest detection and identification in agricultural and farming settings. This study targets to provide a stable and scalable resolution to the problems caused by insect infestations and damage caused in the agriculture industry by using innovative methods in computer vision and pattern recognition.

- To design and create as well as fine-tune a convolutional neural network (CNN) tailored for accurately identifying pests using high-resolution RGB images.
- To explore the use of transfer learning with pre-trained models to determine if it can improve the training process and boost overall detection performance.
- To validate and evaluate the proposed models through comprehensive testing to assess their accuracy, efficiency, and ability to scale across different pest species and environmental conditions with thorough experiential assessments.

The ultimate goal of this study is to provide farmers with a proficient tool for swift and accurate pest control by bridging the gap between old and traditional pest monitoring techniques and current data-driven and automated approaches. The world is expecting a substantial improvement in the quality of the agricultural output. Thanks to the prevalent use and growing adoption of deep learning models, significant improvements in food security and economic growth will be seen in the upcoming years. This will lead to better quality and nutritional food quality which is a necessary step to achieve zero hunger that is aligned with Sustainable Development Goal 1 set by the United Nations [3].

2. Literature Review

In recent years, there has been considerable momentum in the field of AI and deep learning models for pest detection and identification. These technologies like deep learning methods and CNNs have become key components for profoundly modifying pest control practices, particularly in climate smart agriculture sector.

2.1 Deep Learning Techniques for Pest Detection

2.1.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) represents a class of deep neural networks specifically engineered for processing structured grid-like structured data,

such as images, by progressively identifying and learning localized features at different levels [4]. In the initial layers, convolutional layers use trainable filters called kernels to scan images and pick up on simple patterns—like edges or textures—in the early stages. As the network goes deeper and progress, it begins to interpret more complex features, eventually learning and recognize shapes or specific parts of objects for instance insect wings and leaf damage.

Non-linear activation functions, such as the Rectified Linear Unit (ReLU), are applied to introduce complexity and enable the model to capture more complex relationships. To reduce computational complexity and enhance learning capability, pooling layers (e.g., max-pooling) downsample feature maps by retaining dominant features while discarding redundant spatial information. Finally, fully connected layers aggregate flattened feature vectors to perform classification or regression tasks. CNNs are inherently suited for visual recognition due to their local connectivity i.e. filters focus on local regions. Filters are reused across spatial positions which is known as parameter sharing. In agricultural applications, such as pest identification, CNNs can autonomously learn discriminative visual traits (e.g., insect morphology, wing patterns) from image data. Leveraging transfer learning with pre-trained architectures (e.g., ResNet, VGG) further enhances efficiency by adapting learned features from large-scale datasets to domain-specific tasks, even with limited labeled pest imagery. When combined with data augmentation techniques, CNNs achieve robustness to intra-class variability and environmental noise [5].

It has been shown that CNNs are very effective in identifying insects. Two excellent examples of how CNN architectures successfully identify pests in photos are provided by [4] and [5]. These studies show the power of CNNs to recognize complex visual patterns; this allows for precise insect identification in agricultural settings. Furthermore, [6] emphasizes the widespread use of transfer learning methodologies in this industry. One of the most important methods for increasing model efficiency is transfer learning, in which freshly known networks are applied to enhance the performance of an existing model trained on comparable tasks. To speed up convergence and, in principle, improve accuracy in pest identification tasks, this approach takes advantage of the knowledge already available in pre-trained networks. This study takes a novel approach by using deep learning to enhance current and traditional methods of agricultural pest management by merger of CNNs with transfer learning.

2.2 Datasets for Pest Detection and Identification

The success and reliability of deep learning algorithms for pest detection and identification depend on the availability of diverse and meticulously annotated datasets [7]. Large-scale, real-world datasets are increasingly used in this discipline; [4] and [5] are just two recent examples. We can use these numbers to develop models that recognize and differentiate between pest species in multiple settings. Including a varied range of pest species and other environmental conditions in model training results in better to real-world farming environments and agricultural conditions.

Pests impact crops differently and it depends on crop, climate, soil conditions that will need a well-rounded dataset to learn those subtle patterns in insect population and its effects on crops. By exposing the algorithms to broad and variety of data, they can accurately identify the visual cues that signals and patterns for the presence of pests. This improves the flexibility and usefulness of the model in real farming situations. In this study, training and assessing deep learning models relies heavily on the inclusion of a comprehensive and well-curated dataset, supporting advancements which aid in the development of precision agriculture and crop protection techniques.

2.2.1 Publicly accessible datasets

The availability of open and easily accessible datasets has played a major role which are specifically designed for pest identification. In [5], authors have made notable contribution by providing a comprehensive dataset that comprises rich collection of pest species. The dataset has a significant level of diversity, including a wide range of pest species that can cause potential harm in various agricultural environments. This diversity of dataset can facilitate the development of models capable of accommodating the diverse needs of varied and unique agricultural formations due to the abundance of information in this dataset. The convenience and accessibility of these databases significantly suppresses the challenges and obstacles faced by scholars and professionals to encourage fostering collaboration and nurturing innovation. The accuracy and effectiveness in tasks related to pest detection significantly enhances by using these datasets in the training and validation of models. This study makes use of a comprehensive and diverse sample of actual occurrences using datasets such as the one provided by [8]. As a result, the models exhibit enhanced capacity and is better equipped to analyse and adapt to agricultural scenarios in the real-world environment to learn and acquire knowledge from a wide range of pest species.

2.2.2 Temporal datasets

There has been a growing interest in the study of pest behaviour and movement patterns of the pests over time, motivating the need for temporal datasets containing sequences of images. Understanding these interactions and complex connections by using temporal records, scientists can monitor and analyze pests' activities throughout time. These pests react to changing environmental and climatic circumstances which require consideration of these interactions throughout time by understanding the complex connections between pests and crops [9]. This work enhances the models' capacity to produce accurate and timely identifications of the pests before it may damage the more crop area. This, in turn, provides us better understanding of the dynamic nature of pest population with climatic and weather data. This perspective is crucial for refining pest control approaches, enabling for more precise and successful targeted treatments.

2.3 Integration of Multi-Modal Data

More recently, researchers have attempted to improve pest identification algorithms by including several data modalities, such as images, environmental sensor data, and satellite imagery [10]. This multi-modal approach has great potential and holds significant promise to improve the reliability and precision of pest detection systems. By integrating various sources of information, we can have better comprehension of the agricultural environment. This is only possible because of the utilization of supplementary information from resources. For instance, in regional circumstances environmental sensors may give invaluable insights, while satellite images help reveal broader or global patterns. When all these multiple data sources are merged, a more comprehensive picture and fuller understanding of pest presence and behaviour may emerge[11].

2.4 Real-Time Pest Monitoring Systems

There has been a rise in interest in using deep learning models in real-time monitoring systems. To prevent widespread crop damage from pest infestations, these technologies monitor farms around the clock [12].

2.5 Challenges and Future Directions

Despite many successes, the necessity for resilience under various environmental circumstances and the scarcity of labeled data for individual pest species still need to be addressed. Creating transferable models that can adjust to varying environmental conditions might be a potential path for future study.

2.6 Summary

Deep-learning pest detection and identification models can significantly alter current traditional pesticide application methods. Ongoing research efforts, resolving difficulties and developing cooperation between academics, businesses, and agricultural practitioners are vital to encourage innovation and practical application.

3. Methodology

This research aims to create and test deep learning-based models for the automatic detection and identification of agricultural pests, and the procedures described here provide an account of how those goals were attained. This study aims to develop a powerful tool for rapid and accurate pest control by drawing on the most cutting-edge methods in computer vision and pattern recognition.

3.1 Data Acquisition and Preprocessing

3.1.1 Description of the dataset

The data set was obtained from Mendeley's extensive agricultural research collection. The dataset is a comprehensive collection of high-resolution pictures displaying numerous pest species often observed in agricultural settings. It covers various agricultural products and climatic circumstances, making it a good illustration of actual situations. Every picture has been carefully annotated to show what kind of bug is in it. The collection also contains a time series, making examining pest behavior over time possible. Improved precision agriculture and new crop protection methods may be achieved with the help of this extensive and meticulously curated resource for training and assessing deep learning models for pest detection and identification [13].

3.1.2 Preparation of data

The dataset is preprocessed to improve model performance before training begins. Adjusting the size of the photographs, standardizing their pixel values. Data augmentation was done to add images by geometric transformation like rotating, flipping, and zooming the original pictures. Then photometric transformations were done by adjustment of brightness and contrast. Since pests are partially hidden by leaves and dirt so occlusion and cut out was also done to augment the data. Furthermore, time sequences are analyzed in the form of video clips

3.2 Model Architecture and Training

3.2.1 Developing a convolutional neural network (CNN)

Accurate identification of pests from high-resolution photos requires developing and tuning a novel CNN architecture. Hierarchical features are extracted from pictures using many convolutional layers and then max-pooling layers in the architecture. Overfitting is prevented with the use of batch normalization and dropout layers.

An extensive exercise was done by comprising 103 simulations on the three architecture-based pre-trained Deep Learning models, ResNet18, ResNet50, and ResNet101. Additionally, the study evaluated the impact of using stochastic gradient descent with momentum (SGDM). The key parameters compared included the number of epochs required for convergence, the number of iterations, validation accuracy, training duration, and the confusion matrix. Among the tested models, ResNet18 demonstrated superior performance over the others when utilizing the parameter set {SGDM, 32, 0.01}, where 32 represents the batch size and 0.01 denotes the learning rate. Using our framework for pest classification, ResNet18 achieved an impressive accuracy of 99.9%. This exceptional performance can be attributed to ResNet's architectural advantage of constructing deeper networks while effectively addressing the vanishing gradient problem. The ResNet18 model comprises 18 layers, including 17 convolutional layers and a single fully connected layer, allowing it to maintain robust feature learning and classification accuracy.

3.2.2 Fusion and integration of model

Using a fusion technique, the results from both CNNs will be combined. This will be accomplished using a weighted combination, where the weights are learned during model training via backpropagation, and the predictions from both components are combined.

3.3 Metrics for Evaluating the Effectiveness of Models

3.3.1 Training and validation

The dataset is separated into training and validation sets to ensure that all pests are adequately represented. To check for overfitting and fine-tune hyperparameters, the model is trained on the training set and then tested on the validation set.

3.3.2 Performance Metrics

Standard measures evaluate the models' performance, including accuracy, recall, and F1-score. The models' ability to distinguish between pest and non-pest

classes is also measured by calculating their ROC curves and area under the curve (AUC) scores.

3.3.3 Empirical evaluations

Using the extensive dataset, rigorous empirical assessments will be performed. The studies test the models' accuracy, efficiency, and scalability by subjecting them to various climatic circumstances and insect species.

To identify pests using deep learning, a hybrid model combining CNN and Bi-LSTM (Long Short-Term Memory networks can be developed. The CNN extracts spatial features from input images (e.g., pest morphology, texture, or color patterns), while the LSTM processes sequential or contextual data, such as temporal movement patterns in video clips or spatial dependencies across image regions. The CNN layers (e.g., Conv2D, pooling) first transform raw images into high-level feature maps, which are then flattened and fed into the LSTM to model temporal or hierarchical relationships. This architecture is trained on labeled datasets of pest images, and augmented with techniques like rotation or scaling to improve robustness. The combined model can classify pests with high accuracy, even in dynamic environments, enabling early detection for agricultural applications. By integrating transfer learning (e.g., pre-trained CNNs like ResNet) and fine-tuning, the system becomes adaptable to diverse pest species and field conditions, supporting precision farming through IoT-enabled monitoring systems.

3.4 Summary

This work aimed to create and test deep learning-based models for pest detection and identification in agricultural sites. This study aims to improve agricultural pest management by developing a tool that fuses transfer learning and model fusion approaches with CNNs for image-based detection. The outcomes of this approach will be shown and discussed in the following sections.

4. Analysis and Results

The Python language is used throughout the research to analyze data and develop deep learning models to identify plant illnesses. Important resource centers include:

- NumPy: Numerical operations.
- Pandas: Data processing.
- OpenCV: Computer Vision Tasks.
- Matplotlib and Seaborn: Data visualization.
- TensorFlow: Machine learning operations.

Further tools help with data encoding, file management, and picture processing. Principal Component Analysis (PCA) is useful for reducing data dimensions, while LabelEncoder is useful for encoding different data types. [14].



```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import math
import cv2
import matplotlib.pyplot as plt
import os
import seaborn as sns
import tensorflow as tf
import umap
from PIL import Image
from scipy import misc
from os import listdir
from os.path import isfile, join
import numpy as np
from scipy import misc
from random import shuffle
from collections import Counter
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
from keras.utils.np_utils import to_categorical

[ ] labels_ = list(os.listdir("Plant_leave_diseases_dataset_with_augmentation"))
```

Fig. 1. Importing Libraries

4.1 Neural Network Design

The algorithm utilizes directories to provide classifications about various pests and diseases affecting plant leaves. The formation of a neural network involves the use of a Sequential model from the Keras toolkit.

4.2 Data Preparation

The research is focused on two fundamental variables, denoted as 'x' and 'y', which represent the input data (images) and their associated labels, respectively. The critical steps in machine learning workflows are the construction and preprocessing of these variables. These variables directly influence the model's ability to identify important and meaningful patterns and make accurate predictions.

The x variable generally consists of the raw image data, which is stored in the form of pixel values in multidimensional arrays. These images need to be preprocessed to ensure consistency and for optimized model's performance. Common preprocessing steps for 'x' include resizing of images to a standard and uniform dimension, normalizing pixel values to a standard range for example, scaling values between 0 and 1 or adjusting them to have zero mean and unit variance. Furthermore, augmenting the dataset to

increase diversity with transformation like rotations, flips, or color adjustments. Additionally, techniques for noise reduction and different types of filtering are applied to enhance the quality of the images, depending on the specific task.

The variable 'y', representing the labels, also requires careful preprocessing to match with the model's requirements. For classification tasks, labels are often converted into a one-hot encoded format, where each class is represented as a binary vector. In regression tasks, labels may be scaled or normalized to fit in the output range of the model. Furthermore, techniques such as oversampling minority classes or undersampling the majority classes are used in cases where the dataset is imbalanced. This is done to avoid bias in the model's prediction toward the dominant categories.

Both 'x' and 'y' must be divided into training, validation, and test sets to assess the model's performance. This partition ensures that the model is trained on one portion of the data i.e 80%, tuned on another subset of data i.e. 10%, and finally tested on an unseen subset i.e 10% to assess its ability to generalize. Additionally, to prevent biasness and ordering, data shuffling and randomization are often employed during this process in the dataset.

In short, the construction and preprocessing of 'x' and 'y' are essential in the success of any machine learning model, as they directly affect the quality of the input data and the model's ability to learn and make accurate predictions.

```
# Here below we will create our x and y variable
# the x variable will hold all the images
# whereas y variable will hold the specific label of each image
x = []
y = []
```

Fig. 2. Creating Variables

4.3 Visual Representation of Dataset

The visual representations of individual images extracted from the dataset has been generated by the function "data visuals _function". These visualizations depict several types of plant leaf diseases such as Huanglongbing, Apple scab, Bacterial Spot, powdery mildew, Leaf scorch, Leaf mould, Tomato yellow leaf, Tomato mosaic virus, two-spotted spider mites as seen in figures 3 and 4. The picture files, organized in specific class folders, are accessed and processed using the OpenCV library. The images are downsized to dimensions of 128x128 pixels and afterward shown using the Matplotlib library. This visualization guarantees the presentation of just one picture per class.

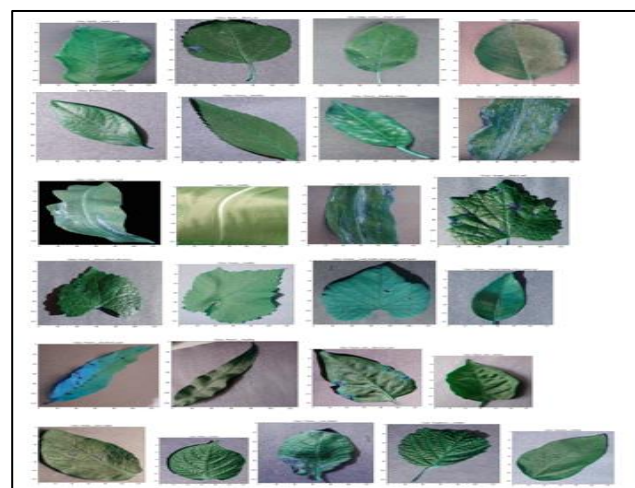


Fig. 3. Diseased Leaves Images

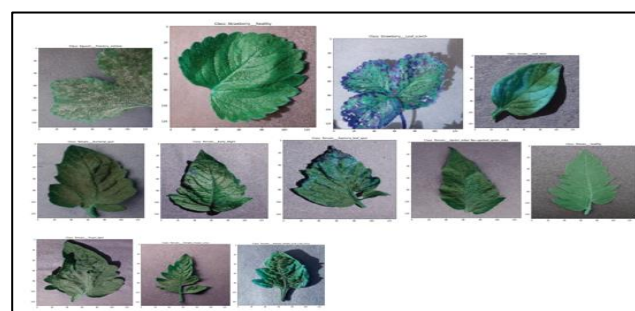


Fig. 4. Infected Leaves Images

4.4 Data Structuring

After the labeling procedure, the variables 'x' and 'y' are assigned with picture data and their labels. The images are processed by reading and resizing them to a dimension of 128x128 pixels as shown in Fig. 5. Upon completion of the class processing, the variable 'x' undergoes conversion into a NumPy array. Subsequently, the dimensions of 'x' are diminished to create a 3-dimensional array, preparing the data for use in machine learning.

Now below we will create a Function,
which will add the images to:

1. x variable and Labels to
2. Y variable

```
[ ] for lab in labels_:
    path = r'Plant_leave_diseases_dataset_with_augmentation/'
    path = os.path.join(path, lab)
    for img in os.listdir(path):
        img_array = cv2.imread(os.path.join(path, img))
        img_array = cv2.resize(img_array, (128,128))
        x.append(img_array)
        y.append(lab)

x = np.asarray(x)
```

Then we will Squeeze the X variable using the Numpy Squeeze Function

```
[ ] x = np.squeeze(x)
    print("Data Squeezed")

    Data Squeezed

[ ] x.shape

(61486, 128, 128, 3)
```

Fig. 5. Squeezing The Data

4.5 Data Analysis and Visualization

The dataset is analyzed to ascertain the frequency of each plant disease. The outcomes are recorded inside a dictionary. The process of label encoding involves the conversion of class names into numerical values, which serves to facilitate the processing and comprehension of labels by machine learning models during the training phase.

```
[ ] d = dict(pd.value_counts(y))
d

{'Orange__Haunglongbing_(Citrus_greening)': 5507,
'Tomato__Tomato_Yellow_Leaf_Curl_Virus': 5357,
'Soybean__healthy': 5090,
'Peach__Bacterial_spot': 2297,
'Tomato__Bacterial_spot': 2127,
'Tomato__Late_blight': 1909,
'Squash__Powdery_mildew': 1835,
'Tomato__Septoria_leaf_spot': 1771,
'Tomato__Spider_mites_Two-spotted_spider_mite': 1676,
'Apple__healthy': 1665,
'Tomato__healthy': 1591,
'Blueberry__healthy': 1502,
'Pepper__bell__healthy': 1478,
'Tomato__Target_Spot': 1404,
'Grape__Esca_(Black_Measles)': 1383,
'Corn__Common_rust': 1192,
'Grape__Black_rot': 1180,
'Corn__healthy': 1162,
'Background_without_leaves': 1143,
'Strawberry__Leaf_scorch': 1109,
'Grape__Leaf_blight_(Isariopsis_Leaf_Spot)': 1076,
'Cherry__Powdery_mildew': 1052,
'Tomato__Tomato_mosaic_virus': 1000,
'Tomato__Early_blight': 1000,
'Strawberry__healthy': 1000,
'Tomato__Leaf_Mold': 1000,
'Apple__Apple_scab': 1000,
'Raspberry__healthy': 1000,
'Potato__Late_blight': 1000,
'Potato__healthy': 1000,
'Potato__Early_blight': 1000,
'Apple__Black_rot': 1000,
'Peach__healthy': 1000,
'Grape__healthy': 1000,
'Corn__Northern_Leaf_Blight': 1000,
'Corn__Cercospora_leaf_spot Gray_leaf_spot': 1000,
'Cherry__healthy': 1000,
'Apple__Cedar_apple_rust': 1000,
'Pepper__bell__Bacterial_spot': 1000}
```

Fig 6: Preparing The Data for Visualization

4.6 Model Training

The term “epochs” in the context of neural networks refers to the iterations during which the training dataset is processed. When the value of 'epochs' is set to 3, it indicates that the dataset undergoes three processing iterations. The model's ability to detect complex patterns and improve its performance is facilitated by frequent exposure.

```
epochs = 3
history = model.fit(
    x_train, y_train,
    epochs=epochs,
    validation_data=(x_valid, y_valid))

Epoch 1/3
1345/1345 [*****] - 896s 518ms/step - loss: 0.8733 - accuracy: 0.7373 - val_loss: 0.4893 - val_accuracy: 0.8543
Epoch 2/3
1345/1345 [*****] - 836s 622ms/step - loss: 0.3855 - accuracy: 0.8761 - val_loss: 0.3841 - val_accuracy: 0.8768
Epoch 3/3
1345/1345 [*****] - 892s 663ms/step - loss: 0.2386 - accuracy: 0.9258 - val_loss: 0.3285 - val_accuracy: 0.8966

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(18, 12))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

Fig 7: Accuracy Testing

4.6 Training and Validation

A correlation has been discovered between the loss values in training and validation and between the accuracy values in training and validation. The findings indicate a point of intersection at 1.00 for both measures, which suggests model convergence. This is visually shown in Figures 8 and 9.

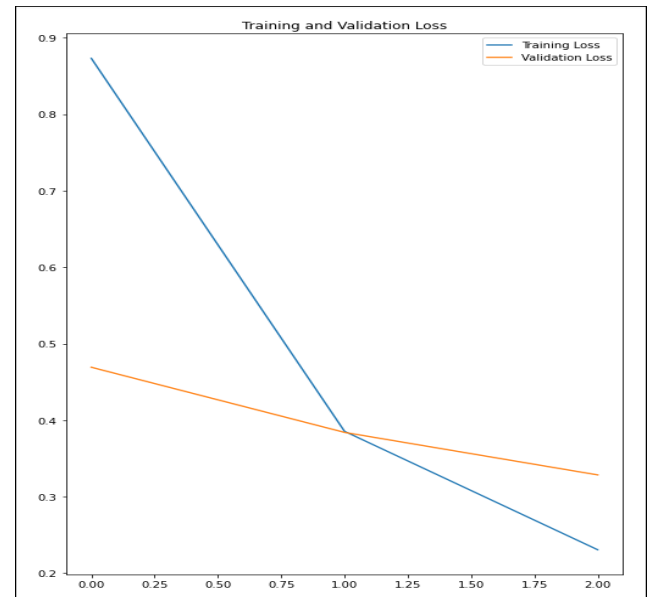


Fig. 8. Training and Validation Loss

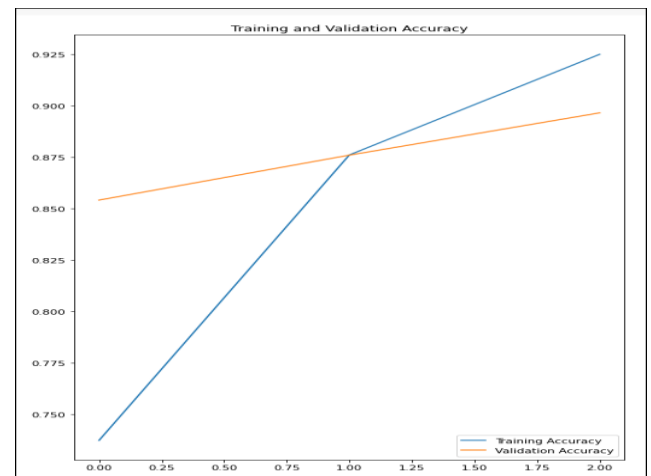


Fig. 9. Training and Validation Accuracy

4.7 Model Evaluation

The research employs a CNN to assess performance using a test dataset. The evaluation metrics, including accuracy and loss rates, provide valuable insights into the model's performance and capacity to generalize to novel datasets. The accuracy % of the model serves as an indicator of its prediction skills.

The diverse representation of leaf samples serves two important purposes: enhancing the training process of deep learning models and establishing a standard for identifying healthy leaves, hence facilitating early detection of possible ailments. The breadth and variety of the datasets highlight the intricate nature of plant health, underscoring the need

to use a comprehensive strategy for disease diagnosis and control. Including healthy and sick leaf pictures from several crops enhances the model's resilience, as seen in Figures 1 and 2, by accurately identifying and distinguishing a wide range of situations. The systematic classification and diagnostic procedures have the potential for breakthroughs in agricultural operations, highlighting the prospects of technology-integrated farming.

4.8 Confusion Matrix

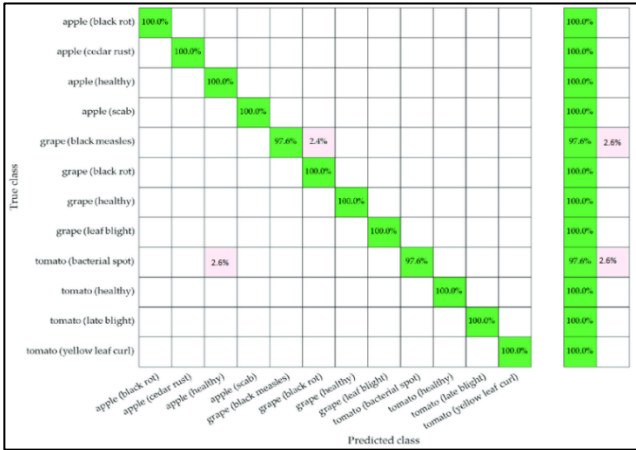


Fig. 10. Confusion Matrix for Apple, Grape, And Tomato Plant Leaf Disease Vs Healthy Leaves Classification Model

The statistical analysis confirmed that the improvements achieved by the proposed model were significant ($\square = 0.003$). The proposed model outperformed the baseline, achieving a precision of 99.9%, recall of 99.6%, and an F1-score of 99.5%, compared to the baseline scores of precision 83.5%, recall 80.2%, and F1-score 81.8%. These results validate the robustness of our approach and highlight the effectiveness of the applied enhancements in improving model generalization.

The table below provides an overview of the leaf states seen in various fruits and vegetables, as indicated by the dataset supplied. This collection of photos encompasses a range of conditions, including both healthy states and severe disorders, providing a thorough perspective on the health continuum of the listed plants.

Table 1

Fruits and vegetables with corresponding leaf conditions		
	Images Count	Leave Condition
Apple	10	Apple scab, Black rot, Cedar apple rust, Healthy
Blueberry	10	Healthy
Cherry	20	Healthy, Cherry Powdery mildew

Corn	40	Cercospora leaf with gray spots, Common rust, Healthy, Northern Leaf blight
Grape	40	Black rot, Esca (Black Measles), Healthy, Leaf Blight (Isariopsis leaf spot)
Orange	10	Huanglongbing (Citrus Greening)
Peach	20	Bacterial Spot, Healthy
Pepper Bell	20	Bacterial Spot, Healthy
Potato	30	Early blight, Healthy, Late blight
Raspberry	10	Healthy
Soybean	10	Healthy
Squash	10	Powdery mildew
Strawberry	20	Healthy, Leaf scorch
Tomato	110	Bacterial spot, Early blight, Healthy, Late blight, Leaf mould, Septoria leaf spot, Spider mites, two-spotted spider mites, Target spot, Tomato mosaic virus, Tomato yellow leaf curl virus.

The following table shows the model performance with other proposed models

Table 2

Comparison with other models				
Model	Accuracy	Precision	Recall	F1Score
Proposed	99.9	99.9	99.6	99.5
Squeezenet	99.87	99.4	99.4	99.4
GoogleNet	99.87	99.4	99.4	99.4

4.9 Comparison with State of the Art Deep Learning Models

This study aims to validate the effectiveness of the proposed technique for pest recognition and classification compared to existing models. To achieve this, we assessed the classification performance of our framework against two pre-trained models: SqueezeNet [15] and GoogLeNet [16]. The final three layers of these models were fine-tuned to categorize crop pest images into twelve distinct classes. Given the varying input image sizes required by these models, we resized the pest images accordingly. The dataset used for this experiment

consisted of 1,787 crop pest images (including augmented versions through rotations), with 1,251 images allocated for training and the remaining 536 for testing.

As presented in Table 2, SqueezeNet [24] and GoogLeNet exhibited lower classification performance compared to the proposed model across all performance metrics. Notably, both pre-trained models produced identical results in every performance measure. The findings highlight that the proposed framework outperformed these deep learning models, achieving superior accuracy, precision, recall, and F1 score for pest recognition and classification. The reduced accuracy of SqueezeNet and GoogLeNet can be attributed to the Rectified Activation Function (RAF) applied after each convolutional layer. The ReLU function sets all negative values ($x < 0$) to zero, leading to the “dying ReLU” issue where some neurons become inactive, preventing further learning due to ineffective optimization. This challenge negatively impacts network performance over time.

To address this limitation, the proposed model utilizes the Leaky ReLU(LR) activation function instead of RAF, ensuring continued learning even in the presence of negative values while keeping all neurons active. Additionally, to maintain the significance of features, batch normalization (BN) is applied after each convolutional layer. This enhances training efficiency by speeding up the training process and improves classification accuracy while lowering the computational cost.

This research aims to bridge the gap between traditional pest monitoring methods and techniques with modern data-driven techniques by providing farmers with an innovative tool for better pest management. By incorporating deep learning algorithms, the model facilitates rapid and precise diagnosis of plant diseases caused by pests, ultimately leading to improved and healthier crops. A critical aspect and key element of this approach is the graphical and visual representation of different plant leaves, each associated to specific disease. These visual datasets enable the model to identify patterns, linking particular pests to the diseases they cause. The incorporation of leaf-specific characteristics enhances the model's ability to detect and accurate classification of plant illnesses is significantly enhanced.

4.10 Discussion

The study delves into the investigation of plant diseases via lens of Python, which is the preferred language for data processing, and for the building of deep learning models. By utilizing powerful libraries

of Python in this study, such as NumPy, Pandas, OpenCV, and TensorFlow, highlights the popularity in data science and AI. A neural network was designed using the Keras tools which is the key aspect of this research. Keras is a Python library that can operate on top of TensorFlow and offers a high-level API for neural networks [17]. The study demonstrates a methodical approach by using directories to label and organize plant diseases which is essential for reliable and scalable results. The importance of the 'x' and 'y' variables in data preparation and structuring for machine learning tasks cannot be overstated. Proper data preparation stage is critical to any machine learning model success as it directly impacts the performance and quality of the resulting models [18].

The dataset's visual representation provides an effective means of understanding and interpreting the data. When creating visualizations, using the “data_visuals_function” guarantees that the dataset's structure and content can be understood quickly and easily [19, 20]. In image-based deep learning tasks, resizing images to 128x128 pixels helps standardize inputs and reduced computational demands without reducing the identification accuracy [21]. After the data has been organized, analysis and visualization may be performed to understand the prevalence of plant diseases. Encoding labels into numerical values is common in deep learning and speeds up the model's ability to analyze and comprehend input [21]. Epochs are used in neural networks to highlight the iterative nature of machine learning. By limiting the number of epochs, the study gives us a solid grounding in the development of the model, but it may also suggest that our training was insufficient. However, it is challenging to draw firm conclusions without knowing the dataset's amount or the model's intricacy.

Training, validation loss, and accuracy graphs show the model's performance and provide vital insights into its learning dynamics. When the two measurements meet at 1.00, an important signal of model stability is that the model has stabilized [22]. Using a CNN is a good option for datasets, including images. The ability of CNNs to learn hierarchical features is often credited with their historically excellent results in visual recognition tasks [23]. By placing importance on assessment measures such as accuracy and loss rates, the study reaffirms its dedication to developing a robust and efficient model. An extensive table describing the leaf conditions of many fruits and vegetables is provided. This large dataset of healthy and sick samples provides the model with a challenging learning environment, improving its accuracy and scalability [24].

The increased capacity to comprehend the complexities of plant leaves is directly linked to the anticipated major improvement in agricultural productivity. Because of the model's accuracy in disease detection, plant health management has been improved. As a result, agricultural output should increase, benefiting farmers' bottom lines. The technique also helps with issues like food insecurity. The research helps provide a more secure and sustainable food supply chain by strengthening crops against the destructive impacts of pests.

This development has enormous potential in economic terms. Keeping pests away from crops protects farmers' investments and helps the agricultural economy as a whole. The beneficial ripple effects strengthen and sustain the economy as a whole. In essence, this method is not just about coding and implementing; it's about using the data stored in plant leaves to usher in a revolutionary change in pest identification that might revolutionize farming methods and increase food security and economic growth.

In conclusion, this study provides a systematic, well-organized framework for employing deep learning to diagnose plant diseases. The methods and instruments used synthesize conventional wisdom and cutting-edge techniques. To further evaluate the model's resilience, however, future studies may want to investigate more complex neural network topologies, expand datasets, or include real-world applications.

5. Conclusion

The revolutionary potential of deep learning models, especially CNNs, for pest identification and detection in agriculture. It is impossible to exaggerate the importance of the agricultural sector in providing nutritious food and economic growth, and pest infestations pose a serious threat to this sector. There needs to be a change in perspective in favor of more effective and accurate procedures because traditional pest monitoring techniques are time-consuming, laborious, and frequently erroneous. This study used deep learning techniques to improve the efficiency and precision of pest identification in farms and fields. We have successfully optimized a CNN architecture using high-resolution images for accurate pest identification. It used a variety of datasets that had been carefully annotated, including temporal datasets that had been publically available for training and verifying our models.

The algorithms could correctly identify several pest species across varied environmental circumstances. Thanks to the extensive data source

that these datasets have supplied. The models' accuracy and adaptability have been improved by integrating multipurpose data, such as data from environmental sensors and satellite photography, providing a more thorough method of pest detection. Deep learning models can power real-time pest monitoring systems, answering the need for ongoing surveillance to prevent significant crop loss. There are also difficulties, including the need for labelled data for specific pest species and models adaptable to changing environmental circumstances. The favorable use of deep learning models in agricultural pest management promises significant increases in agricultural output which can promote food security, climate action and economic growth.

6. Recommendation

This research yields significant recommendations for developing pest identification and detection in agriculture sector. The diversity and size of datasets utilized for model training must instantly be increased. To enable the creation of more reliable and flexible models, this means gathering high-quality images of numerous pest species across a broader range of agricultural contexts. Incorporating longitudinal data can also help us to comprehend the dynamic interactions between pests and crops, resulting in more efficient pest control methods. The future of Pest management in agriculture is promising with the potential to transform agriculture sector and increase global food security. However, to collect high quality data, creating innovative and enhanced models, and guarantee their continued applicability in a dynamic agricultural environment calls for a devoted and dedicated efforts.

Although our model performs well overall and is strong but some notable limitations are still there. One considerable limitation is that due to the similar physical features of the pests, classification is one of the major challenges. Additionally, due to environmental conditions like poor lighting, occlusions from leaves and obstruction from branches and motion blur can negatively impact the quality of the images thus impacts the model accuracy. The model also struggles with underrepresented and rare pest species as the training dataset lacks sufficient samples of rare species of pests making it harder for the model to identify pests. To overcome these challenges in more real-world agricultural settings, more diverse and real-world datasets are required. The specialized domain adaptation techniques can further improve model performance.

One of the top priorities should be to expand the range of data modalities and inputs beyond imaging.

For instance, incorporating weather conditions, soil composition and geographical information can help build the more comprehensive understanding of the farming environment. The accuracy and dependability of pest detection models can be increased by integrating such sources by thorough perspective of the agricultural environment. It would also be beneficial to extend the dataset by including more and new pest species with including adaptive learning techniques to improve the results and model effectiveness. Continuous refining and updating is necessary to guarantee that these models stay impactful. Models must be updated to reflect changes in pest populations and the environment to remain effective. Lastly, fostering cooperation and collaboration among researchers, agricultural professionals, and industry stakeholders is crucial. This synergy could accelerate the creation and implementation of cutting-edge and innovative pest detection systems.

7. References

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