PlantifyAI:

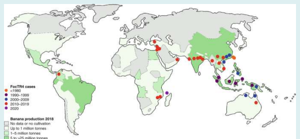
A Novel Convolutional Neural Network Based Mobile Application for Efficient Crop Disease Detection and Treatment

Samyak Shrimali

Problem Statement

Modern practices and technology have given humans the ability to produce enough food to meet the demand of more than 7 billion people. But food security remains a prominent issue as it is threatened by climate change, decline in pollinators, and most importantly crop diseases. Crop diseases are not only a threat to global food security but also affect the lives of millions of smallholder farmers who depend on healthy yield [1]. Around the world, more than 80% of agricultural production is generated by farmers, and over 50% of their yield is lost due to pests and pathogens. This leads to mass disruption in food supply and a large number of hungry people, specifically the farmers and their households who account for the largest fraction of hungry people (50%) [2]. Fortunately, these diseases can be limited and cured by identifying them as soon as they appear on a crop. Identifying disease can lead to quicker interventions that can be implemented to reduce the effects of crop diseases on food supply

Graph on right shows the current state of food security in countries around the world



Research

Current practices for crop disease identification are based upon significant support from agriculture organization and local plant clinics, but millions around the world do not have access to these resources, especially farmers in developing and underdeveloped countries. More recently internet-based video chatting diagnosis tools have appeared, but these tools do not consider that more than 40.5% of the world's population is lacking internet access [3][4]. Current solutions used for crop disease identification are ineffective, at times inaccurate, and not cost-effective. The agriculture industry is in dire need of a tool that can that efficiently and accurately diagnose crop diseases while being free, easy-to-use, and widely accessible.

Figures on left show current solutions implemented for crop disease diagnosis

Smartphones in particular can be used for this application since they provide high resolution displays, efficient computing power, and a built-in set of accessories (ex. cameras, speakers, etc.). Smartphones are also widely accessible, as of 2020, more than 66.7% of the world's population owns a smartphone, and this number is projected to keep increasing [5]. The combined factors of widespread smartphone usage, access to high-definition cameras and computing processors in mobile devices lead to a situation where disease diagnosis based on automated image recognition, if technically feasible, can be made available at an unprecedented scale and can significantly increase world food security.

Engineering Goal/Design Criteria

The goal of this project is to a develop a free, easy-to-use, and widely accessible deep learning-based application that makes immediate crop disease diagnosis, provides farmers with steps to mitigate the identified disease, and guides farmers toward better future disease prevention.

Below is the key design criteria:

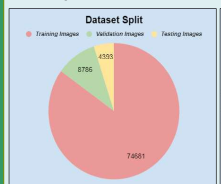
- The application should be easy to use and navigate and have a simple user interface
- The application should be able to identify and detect crop diseases with 90+% accuracy
- The application should use deep learning algorithms to conduct checks and should be scalable for usage in developing and underdeveloped countries
- The application should work without wireless connection since most farmers in developing and underdeveloped countries do not have access to internet

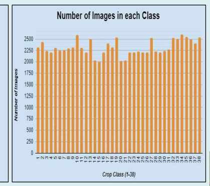
Application Development

CNN-Based Deep Learning Check Development

A. Dataset

To develop an optimal model, first, an image dataset was obtained and preprocessed. This dataset was acquired from the PlantVillage database and consisted of 87,860 leaf images referring to 38 classes. Images were classified in diseased and healthy categories. All the images were resized to 224 × 224 pixels. The dataset was split into a ratio of 85:10:5 for training, validation, and testing, respectively. The figures below showcase the dataset characteristics.

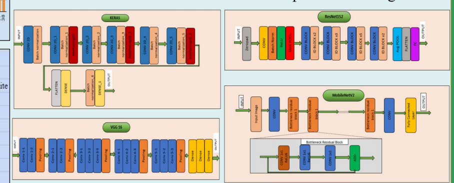




PlantVillage Dataset (38 Classes)			
Apple_scab	Grape_black_rot	Potato_late_blight	Tomato_septoria_leaf_spot
Apple_black_rot	Grape_black_measles	Raspberry_healthy	Tomato_spider_mites_two-spotted_spider_mite
Apple_cedar_apple_rust	Grape_leaf_blight	Soybean_healthy	Tomato_target_spot
Apple_healthy	Grape_healthy	Squash_powdery_mildew	Tomato_mosaic_virus
Blueberry_healthy	Orange_haunglongbing	Strawberry_healthy	Tomato_yellow_leaf_curl_virus
Cherry_powdery_mildew	Peach_bacterial_spot	Strawberry_leaf_scorch	
Cherry_healthy	Peach_healthy	Tomato_bacterial_spot	
Corn_gray_leaf_spot	Pepper_bacterial_spot	Tomato_early_blight	
Corn_common_rust	Pepper_healthy	Tomato_healthy	
Corn_northern_leaf_blight	Potato_early_blight	Tomato_late_blight	
Corn_healthy	Potato_healthy	Tomato_leaf_mold	

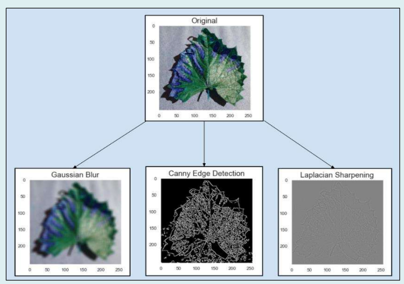
B. Neural Network Architectures

Four different convolutional neural networks were designed all based on different architectures, VGG-16, ResNet-152, MobileNetV2, and a custom Keras configuration. These are considered four of the most accurate, efficient, and effective model architectures for computer vision tools and multiclass classification problems. The main layers these model architectures utilized were convolutional layers to extract features from the images for identification, max polling layers to down sample the size of the training data, flatten layers to collapse the spatial dimensions of the input into channel dimensions, and dense layers to align the extracted features to certain categories. To ensure that none of these models overfit the dataset (meaning they do not pick up the noise or random fluctuations between images) additionally to these layers, dropout and regularization layers were added to monitor the neural network's speed of learning.



C. Feature Extraction

Through the usage of the CV2 library, image processing filters were also applied during the training, validation, and testing process to explore efficient and precise feature extraction. The image filters applied were Gaussian Blur, Laplacian Sharpening, and Canny Edge Detection [7].

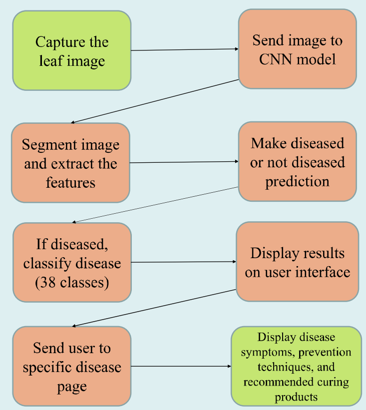


$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

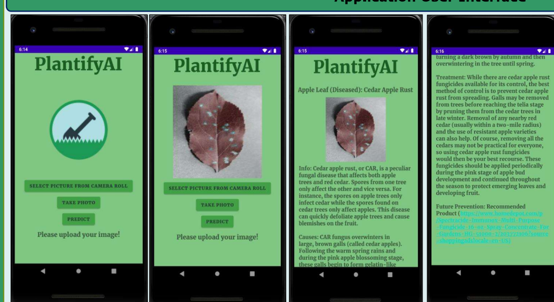
$$C(\sigma) = \frac{1}{2\pi\sigma^2} e^{\left(-x^2-y^2\right) \times \frac{1}{2\sigma^2}}$$

$$L(f) = \frac{\partial^2 f}{\partial^2 x} + \frac{\partial^2 f}{\partial^2 y}$$

D. Application Workflow



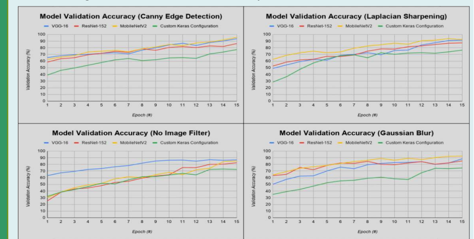
Application User Interface



The app's user interface consists of two main options for crop diagnosis, the user can either select and upload a crop photo from their camera roll or take a real-time image. After an image has been received by the application, the application runs the classification model and returns the crop's disease diagnosis. Depending on the diagnosis, the user is presented with details on the disease's common symptoms, prevention techniques, and recommended products to use to reduce disease and cure the crop. Additionally, users also have the option to tag photos with specific disease labels once the diagnosis is given, this allows them to keep track of already tested and identified crops.

Results

Multi-level testing and data analysis has been conducted while developing this application. In the initial neural network development stage, 16 different neural networks were designed, trained, validated, and tested (each based on a different model architecture and image processing filter). MobileNetV2 using the Canny Edge Detection filter was chosen as the most optimal model for PlantifyAI since it had the highest classification accuracy of 95.7%.



16 different convolutional neural networks (4 unique architectures with 4 unique image processing filters) were tested and analyzed to find an optimal choice for PlantifyAI's diagnostic tool. The above graphs are a comparison of all the model's validation accuracies. They showcase that MobileNetV2 using Canny Edge Detection filter achieves the highest accuracy and therefore was selected.

Model Architecture	Training Image Filters	Accuracy	Precision $\left(\frac{TP}{TP+FP}\right)$	Recall $\left(\frac{TP}{TP+FN}\right)$	F1 Score $\left(2 \times \frac{P \cdot R}{P+R}\right)$
VGG	Gaussian Blurred	88.4%	90.2	90.5	90.3
	Laplacian Sharpening	91.5%	90.5	92.1	91.3
	Canny Edge detection	93.6%	92.7	91.2	91.9
	None	86.8%	86.2	85.8	86.0
ResNet152	Gaussian Blurred	85.3%	83.5	86.3	84.9
	Laplacian Sharpening	87.3%	89.2	88.4	88.8
	Canny Edge detection	86.3%	82.5	85.2	83.8
	None	82.5%	80.2	81.1	80.6
MobileNetV2	Gaussian Blurred	92.4%	92.5	94.2	93.3
	Laplacian Sharpening	92.1%	92.4	91.8	92.1
	Canny Edge detection	95.7%	96.4	95.8	96.1
	None	85.2%	86.4	85.2	85.8
Custom Keras configuration	Gaussian Blurred	74.6%	75.2	76.8	76.0
	Laplacian Sharpening	76.4%	72.5	77.2	74.8
	Canny Edge detection	77.3%	71.6	79.2	75.2
	None	72.5%	79.1	72.5	75.7

Additionally, to validate the model selection, each model's precision, recall, and F1 score was calculated, MobileNetV2 using Canny Edge Detection filter topped all the categories, it had an accuracy of 95.7%, precision value of 96.4, recall of 95.8, and F1 score of 96.1. *(TP = True Positive, FN = False Negative, FP = False Positive, P = Precision, R = Recall)*

Conclusion

This project aimed to develop a free, easy-to-use, and widely accessible mobile application that efficiently and accurately diagnoses crop diseases to increase human food security and heal/protect the environment. In conclusion, through comprehensive testing and analysis of results, PlantifyAI was a success. It can diagnose 26 diseases of 14 crop species very accurately and in real-time, with its model having a high accuracy of 95.7%. Furthermore, PlantifyAI provides treatment steps, common symptoms, and access to recommended curing products for each disease. It allows farmers all around the world to produce crops in an ecologically sustainable way while not having to worry about unknown crop diseases. It has the ability to save thousands of lives every year and promote the usage of proper agricultural tools in developing and underdeveloped countries.

With minor changes, PlantifyAI can be used for many purposes, it can be converted into a web application for easy access to concurrent multi-image diagnosis, or it can be integrated with a drone for real-time automated surveillance of farms, the possibilities are endless

References

[1]. Anderson, P. P. (2001). The future World food situation and the role of plant diseases. *The Plant Health Instructor*. doi:10.1094/phi-i-2001-0425-01

[2]. Pests and diseases cause worldwide damage to crops. (2019, February 11). Retrieved April 04, 2021, from https:/ californiaagtoday.com/pests-diseases-cause-worldwide-damage-crops

[3]. Yi, F., & Ramasamy, R. (n.d.). Current and prospective methods for plant disease detection. Retrieved April 04, 2021, from https://pubmed.ncbi.nlm.nih.gov 26287253/

[4]. New standards to curb the global spread of plant pests and diseases. (n.d.). Retrieved April 04, 2021, from http: /www.fao.org news story en/item 1187738 icode

[5]. Gaubys, J. (n.d.). How many people have smartphones in 2020. Retrieved April 04, 2021, from https://www.oberlo.com/statistics how-many-people-have-smartphones#:~:text=Latest%20figures%20show%20an%20increasing,rate%20is%20at%2045.4%20percent.

[6]. Emmanuel, T. (2018, October 30). PlantVillage dataset. Retrieved April 04, 2021, from https://www.kaggle.com/emmarex plantdisease

[7]. Image processing in OpenCV. (n.d.). Retrieved April 04, 2021, from https://docs.opencv.org/master/d2 d96/tutorial_py_table_of_contents_imgproc.html

[8]. Gour, R. (2019, April 30). The essential guide to Learn Tensorflow mobile and TENSORFLOW LITE. Retrieved April 04, 2021, from https://towardsdatascience.com the-essential-guide-to-learn-tensorflow-mobile-and-tensorflow-lite-a70591687800

[9]. Disease Database. (2020, October 22). Retrieved April 04, 2021, from https:/ arborjet.com/

[10]. Organic gardening database. (2020, April 15). Retrieved April 04, 2021, from https://www.planetnatural.com/

Campbell, C. (1990). *Introduction to plant disease epidemiology*. New York: J. Wiley.

Carlton, R. (2019). Food and energy security sustainable intensification special issue editorial. *Food and Energy Security, 8*(4). doi:10.1002/fes3.184

Carroll, C., Carter, C., Goodhue, R., & Lawell, C. C. (2017). Crop disease and agricultural productivity. doi:10.3386/w23513

David Moore, G. (2019, July 01). 21st century guidebook to FUNGI. Retrieved April 04, 2021, from http://www.davidmoore.org.uk/21st_Century_Guidebook_to_Fungi_PLATINUM/Ch14_01.htm

Food security. (n.d.). Retrieved April 04, 2021, from https: /www.usda.gov/topics/food-and-nutrition/food-security

Keras IO API Docs. (n.d.). Retrieved April 04, 2021, from https://keras.io

Khandelwal, R. (2020, June 15). A basic introduction to tensorflow lite. Retrieved April 04, 2021, from https://towardsdatascience.com/a-basic-introduction-to-tensorflow-lite-59e480c57292

Mammone, R. J., & Zeevi, Y. Y. (1991). *Neural network: Theory and applications*. Estados Unidos: Academic Press.

Preventing food losses and waste to achieve food security and sustainability. (2020). doi:10.1201/9780429266621

Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. (1970, January 01). MobileNetV2: Inverted residuals and Linear bottlenecks. Retrieved April 04, 2021, from https:/ openaccess.thecvf.com/content_cvpr_2018 html/Sandler_MobileNetV2_Inverted_Residuals_CVPR_2018_paper.html

Savary, S., Ficke, A., Aubertot, J., & Hollier, C. (2012). Crop losses due to diseases and their implications for global food production losses and food security. *Food Security, 4*(4), 519-537. doi:10.1007/s12571-012-0200-5

Shen, J., & Shafiq, M. O. (2019). Learning mobile application usage - a deep learning approach. *2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA)*. doi:10.1109/icmla.2019.00054

Sivaprakasam, K., & Seetharaman, K. S. (1994). *Crop diseases: Innovative techniques and management*. Ludhiana India: Kalyani.

Stoetzer, E. (n.d.). Crop protection network launches new disease loss estimate tool. Retrieved April 04, 2021, from https://crops.extension.iastate.edu/blog ethan-stoetzer/crop-protection-network-launches-new-disease-loss-estimate-tool

Transforming food systems for affordable healthy diets. (2020). Rome: FAO.

Venkatesan, R., & Li, B. (2018). *Convolutional neural networks in visual computing: A concise guide*. Boca Raton, FL: CRC Press.

Zhang, C., Patras, P., & Haddadi, H. (2019). Deep learning in mobile and wireless networking: A survey. *IEEE Communications Surveys & Tutorials, 21*(3), 2224-2287. doi:10.1109/comst.2019.2904897