

# D-KAP: A Transfer-Learning and Handcrafted Features Framework for Mango Leaves Disease Classification and Detection

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**Abstract**—Agriculture is an important sector in the world economy, but plant diseases pose a serious constraint on productivity and quality of crop plants. Mangoes are an important crop in Pakistan, and diseases such as Mango Scab, Mango Rot, and Alternaria leaf blotch can impact yield. Manual inspection by the farmers is labor intensive, time consuming, and has a high risk of errors, and automated solutions are needed. This research presents the D-KAP framework, an automated system designed for the early detection and classification of mango leaf diseases using deep learning. A set of 419 high-resolution images was specifically collected from the Uch Sharif district of Bahawalpur and included healthy as well as diseased leaves in different environmental conditions. The study adopts transfer learning using the Convolutional Neural Network (CNN) architectures ResNet-50 and Xception. Image preprocessing is used to improve feature visibility. The experimental results show that the ResNet-50 model had the highest classification accuracy of 80% compared to Xception model with a classification accuracy of 78.1%. “The framework also investigates handcrafted feature extraction techniques, including Speeded-Up Robust Features (SURF), Histogram of Oriented Gradients (HOG), and Local Binary Pattern (LBP), and evaluates their performance under increasing dataset complexity. The proposed framework offers a comprehensive and effective solution for farmers, allowing them to manage various diseases effectively and potentially boost their crop yields.

**Index Terms**—Mango Disease, Deep Learning, CNN, ResNet-50, Xception and Image Processing

## I. INTRODUCTION

AGRICULTURE has an important role in ensuring food security and economic development, and plant diseases are an important factor in crop yield and quality. Plant diseases are usually identified by farmers and plant specialists through visual means, but this can take a long time and may be influenced by human knowledge and judgment. The reliable detection and classification of plant diseases with image processing techniques is of great importance [1].

Using image processing and computer vision is an alternative solution to plant disease automated identification. Previous image-processing studies showed that the colour attributes of an image can be used in order to detect disease symptoms, while machine learning algorithms could enhance this automated classification.

A method for automatic detection of plant disease based on image processing [2]. Likewise, this showed that the features of shape, veins, color and texture are useful in identifying and classifying plants [3].

Convolutional Neural Networks (CNNs) are an important method in the field of image-based plant disease detection as they are able to learn relevant features automatically from images. A CNN based approach for identification of mango leaf diseases with accuracy of 96.67% and showed the potential of CNNs for the distinction of disease symptoms of mango leaves [4].

There have been several studies that have explored automated mango disease detection using machine learning and deep learning methods. A comparison is performed between CNN and Alexnet for mango and potato leaf detection [5], while adopted K-means clustering for feature extraction and SVM for classification, with an accuracy of 94.13% [6]. In mango disease identification, by using deep residual network (DRN) with contrast enhancement and transfer learning, that showed 88.46% accuracy [7].

However, so far, most of the proposed solutions have been targeted to specific diseases, small data sets, or specific image processing and classification methods. Availability of appropriate mango disease data and development of reliable automated systems are thus still research needs. For instance, the research highlighted the need for comprehensive mango disease datasets and created MangoLeafBD with 4000 images of healthy leaves and various mango diseases [8].

To solve this issue, this paper proposes an automated mango leaf disease analysis approach using image processing, transfer learning, handcrafted feature extraction and disease-region

detection framework, referred to as D-KAP. For this purpose, this study proposes an automated method for mango disease analysis based on image processing, transfer learning, handcrafted feature extraction and detection of disease region (D-KAP). In the Uch Sharif district of Bahawalpur, Pakistan a novel dataset of 419 mango leaf images was gathered at high resolution. The data consists of healthy and diseased leaves of mango trees with Mango Scab, Mango Rot and Alternaria leaf blotch. Images were taken with a variety of mobile devices in May, June, and July with varying natural image-acquisition conditions (such as illumination, background, camera distance, and orientation of the leaves). Collected images were preprocessed and then evaluated two CNN models (Resnet-50 and Xception) that were trained by transfer learning.

It also independently evaluated SURF, HOG and LBP to explore the performance of handcrafted feature extraction methods with the acquired mango leaf images without using the CNN-based feature representations. Additionally, a separate Anthracnose detection experiment is also performed using annotated positive and negative samples with a cascade-based detection procedure. A separate Anthracnose detection experiment is additionally run with annotated positive and negative samples along with a cascade-based detection procedure. The integrated framework is proposed with these approaches to give an integrated analysis of classification of mango leaf disease and detection of disease region based on a local dataset.

This study has three major contributions. To achieve this purpose, a mango leaf image dataset was developed for the first time, as images were collected from Uch Sharif, Bahawalpur, and thus, the developed image dataset represented the investigated agricultural conditions in the region. Second, two CNN architecture based on transfer learning, ResNet-50 and Xception, were compared for multiclass mango leaf disease classification. Third, handcrafted feature extraction methods and an independent Anthracnose detection method were explored to supplement the classification analysis using deep learning. The overall goal is to assess the feasibility of an automated and regionally representative system for mango disease analysis and to serve as a basis for the development of practical agricultural systems for disease detection.

## II. LITERATURE REVIEW

The study of mango disease detection using image processing, conventional machine learning and deep learning has been studied before. Early image-based approaches were mainly dedicated to the recognition of visual features of plant diseases and application of classification algorithms to detect diseased areas. The research proposed an image-processing based method to automatically recognize visual symptoms of plant diseases [2] and [1] reviewed image-processing techniques for plant leaf disease detection. These studies set the stage for the need for image-based analysis in automated disease identification. Later, a few studies used the traditional machine learning approach to mango disease recognition. In [5] compared CNN and AlexNet for mango and potato leaves disease detection based on dataset of 4004 images and found

that the accuracy of the learning of AlexNet is better than CNN architecture used by them. The study [6] presented an SVM classifier-based mango disease recognition approach with feature extraction by K-means algorithm, which was found to be 94.13% accurate.

There has also been a study on using image-processing and feature-based classification methods for specific mango diseases. To classify three mango diseases and healthy leaves, created a deep residual network that incorporates contrast enhancement and transfer learning. They found an accuracy of 88.46% and thus proved the viability of using image enhancement techniques along with deep learning [7]. A successfully detected anthracnose, fruit borer and sooty mold in rice crop images using multi-SVM and GLCM-based image processing method with 85% accuracy [9]. A contrast enhancement and SVM classification-based mango disease detection system. The proposed study was done on 92 samples and achieved 90% accuracy, showing the effectiveness of the extracted characteristics of images for the classification of disease [10]. Also [11] studied the recognition of mango leaf disease using Neural Network Ensemble (NNE) and Machine Learning (ML) methods to get the diagnosis of the disease faster than visual inspection.

An image processing-based mango disease recognition system. In the proposed approach, the disease classification successfully detected and classified the images with a rate of 68.89% after the segmentation and pre-processing of the smartphone images [12]. In [13] created a CNN-based system to detect anthracnose in Mango. They used 364 images (sick and healthy) in their dataset and the classification accuracy they got is more than 70%.

Later works have been concentrated on deep learning, on larger datasets, and on more practical applications for detecting diseases. To solve the issue of availability of mango disease data in a standardized and public repository, built a comprehensive mango image dataset named MangoLeafBD [8]. Enhancing the accuracy of mango disease detection and pesticide recommendations, created a deep learning-based smartphone app [14].

An automated mango disease identification and classification system using deep learning method with the inclusion of ecological information [15].

Machine learning and image-based features to develop an automatic system for detecting mango diseases. Their data consisted of images in several categories and DenseNet169 was able to attain 97% accuracy, 96% recall and 96% F1 score. The study also integrated the trained model into an Android app for actual identification of the disease [16].

The overall findings from the reviewed studies showed the evolution of traditional image-processing and feature-based machine learning techniques to CNNs and advanced deep learning techniques for mango disease detection. While good classification performance has been reported, there are significant variations among the available studies in the dataset, disease categories, image conditions, and model architecture. Most approaches are created on the basis of small or specific sets of data and are limited in scope of diseases. These constraints suggest the need for further development of more robust systems for the classification of mango diseases using

images, which can accommodate multiple disease categories in similar experimental conditions.

### III. METHODOLOGY

The purpose of this section is to describe the systematics and technology used for detection and identification of mango leaf disease. The system proposed is called the D-KAP (Diagnostic Knowledge Augmented by Processing & Deep Learning) system, a combination of advanced image processing and deep learning architectures to offer an automatic diagnostic solution.

#### A. System Workflow

The proposed system, known as the D-KAP system, consists of four processes: image acquisition, image preprocessing, transfer learning-based disease classification, and final disease identification. This research process includes four main steps: Data collection and preparation, image preprocessing, model building with transfer learning, and classification at the end.

In the first phase, the mango leaf images were collected in the region of Uch Sharif, Bahawalpur to get a dataset that is representative of the targeted area. The second phase consisted of resizing, augmentation, image processing and normalization of the captured images. In the 3rd stage, the transfer learning approach was adopted to adapt the pretrained CNN architectures to the problem of classification of mango diseases. Finally, the trained models were applied to classify the mango leaf images to the investigated healthy and diseased classes. The framework also includes handcrafted feature extraction and Anthracnose recognition as an independent process that gives extra analysis of the image features related to the disease.

The working flow of the proposed D-KAP architecture is shown in Fig. 1.

TABLE I  
DEVICES FOR CAPTURING MANGO SAMPLES

| Mobile Brand | No. of Cameras | Images Captured |
|--------------|----------------|-----------------|
| Redmi 9      | 4              | 109             |
| OnePlus      | 2              | 97              |
| Realme C1    | 2              | 80              |
| iPhone       | 2              | 103             |
| Redmi 8      | 4              | 30              |

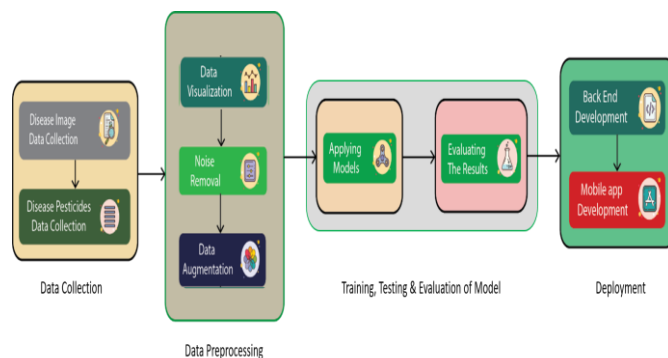


Fig. 1. Workflow of the proposed system

#### B. Dataset

A new dataset was created for this research as no specific benchmark dataset was available for the Uch Sharif and Bahawalpur region for the considered mango varieties. A total of 419 high-resolution images were collected in May, June, and July in Uch Sharif district, Bahawalpur, Pakistan. The data set comprises healthy mango leaves and leaves with three diseases – Mango Scab, Mango Rot and Alternaria leaf blotch. Using a variety of mobile devices to take images, leading to variations in camera and sensor characteristics. Images were taken under natural field conditions, making the illumination, background appearance, camera-to-leaf distance, and leaf orientation varied. These variations are significant because they can change the colour and visibility of the disease symptoms and/or provide irrelevant visual information in the background. Differences in camera distance may lead to differences in the relative size of the disease symptoms as seen in the photograph, and differences in leaf orientation may lead to differences in the spatial appearance and shape of the disease symptoms as seen in the photograph. These changes in the acquisition enable a more realistic evaluation setting and enable the models to be evaluated on images that are not completely uniform in appearance.

The distribution of images based on the media used for data collection is shown in Table I. Multiple devices offer variations in image acquisition conditions and enable the classification models to be tested on images with variations in camera characteristics. Fig. 2 shows the sample of normal mangoes from our dataset.

#### C. Image Pre-processing and Augmentation

The images collected were subjected to image pre-processing steps to ensure a standardized representation of the images for training the classification models. To ensure a consistent input size for the chosen CNN architectures, all images were scaled down to  $224 \times 224$  pixels.

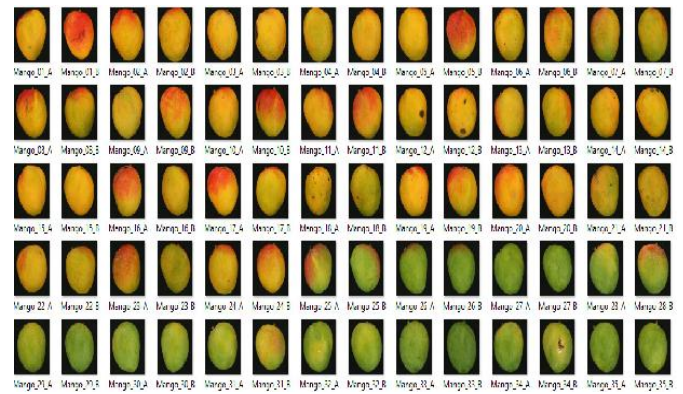


Fig. 2. Sample of normal mangoes

The sample of effected mangoes shows is Fig. 3.

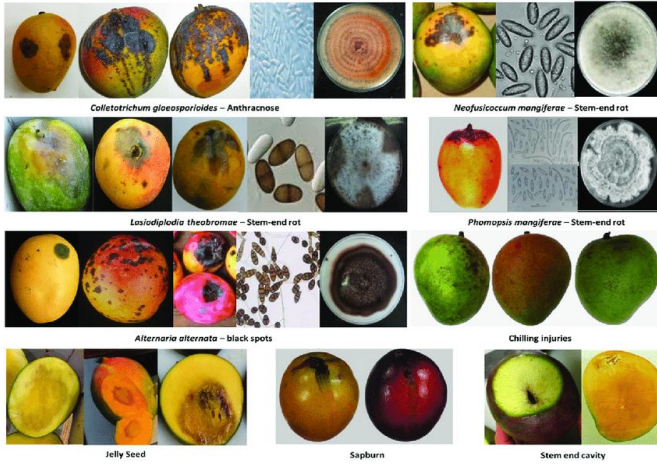


Fig. 3. Sample of effected mangoes

The augmentation operation of image flipping was used in order to create extra variation in the training set. The images were then subjected to image-processing and normalization procedures to prepare the images for feature extraction and classification. The pre-processing was designed to give a standardized image representation while preserving the visual characteristics related to disease symptoms. While normalization and resizing help to increase the uniformity of input, there can still be some differences in the images that are due to the lighting, background, distance to the camera, and leaf orientation. These differences were thus taken into account when assessing the robustness and generalizability of the classification models. Furthermore, image segmentation and Region of Interest (ROI) identification were integrated into the detection module to identify the regions of interest in the image that could be used to train the detector for the disease.

#### D. Computational Environment and Tools

An experiment was conducted on a system that has 16 GB RAM with Windows 10 Pro OS. The main development environment was Visual Studio Code, and package management was provided through the Anaconda distribution. The deep-learning models were built and trained using TensorFlow and Keras, and numerical computation and data manipulation were conducted with the help of NumPy and Pandas. Data visualization and performance graph generation were done using the 'matplotlib' package. The web-based runtime environment Google Colab was also used to supply GPUs for more demanding training tasks.

#### E. Proposed CNN Architectures

In the D-KAP framework two architectures of the Convolutional Neural Network (CNN) architectures: ResNet-50 and Xception are evaluated with transfer learning. ResNet-50 is a deep residual network with a number of residual connections to assist in learning deep representations and solving the vanishing gradient problem. It features convolutional, pooling and fully connected classification layers with softmax activation at the end for the classification output. Xception, on the other hand, uses depthwise separable convolutions and is optimized for performing deep feature

learning efficiently. The model pretrained architectures were fine-tuned and adapted to the custom mango leaf dataset to use for transfer learning. The aim of the use of these two architectures was to compare their performance of distinguishing healthy and diseased mango leaf images under the regional dataset conditions.

#### F. Feature Extraction

The various features extracted by handcrafted methods were evaluated independently to analyze the visual traits of the mango leaf images, with the exception of the CNN-based transfer learning experiments. Three algorithms of feature extraction, namely Speeded-Up Robust Features (SURF), Histogram of Oriented Gradients (HOG), and Local Binary Pattern (LBP) were considered. The handcrafted features were not fed into the learned features of ResNet-50 or Xception and not used as extra inputs to the CNN classifiers. Instead, SURF, HOG and LBP were tested as independent feature extraction methods and compared in their behavior when the complexity of the datasets is increased. Local interest points were identified using SURF, local gradient and structural information using HOG, and local texture patterns using LBP. Therefore, the CNN-based transfer learning experiments and handcrafted feature experiments are two complementary but independent analyses in the framework of D-KAP. CNN models were used to classify the disease, while SURF, HOG and LBP were tested independently to study the performance of traditional image descriptors.

#### G. Anthracnose Detection

A cascade-based detection procedure was carried out to detect Mango Anthracnose in a separate experiment. The image processing started from image pre-processing and Region of Interest (ROI) identification. To annotate the parts of the images that contain the disease, the mango images were annotated using the Image Labeler application. The annotations were used to create positive samples to be used for training the detectors, and other images that were separately collected but not containing the region with the target disease were used as negative samples. The positive and negative samples were used to train the cascade detector. The detector was then tested for its performance with test images to detect the Anthracnose regions and to visualize the detected regions through bounding boxes. The performance of the detection system was then tested with a set of unseen images to measure the disease region detection accuracy.

## IV. EXPERIMENTAL RESULTS

The results from the experiments are analyzed in detail in this section, using the D-KAP framework. The performance of different feature extraction algorithms is evaluated and the comparison of the accuracy of classification of deep learning architectures: ResNet-50 and Xception.

#### A. Experimental overview and ROI analysis

A set of experiments has been performed to evaluate the effectiveness of the D-KAP framework for detection and

classification of mango leaf diseases under the considered image-acquisition conditions. The image preprocessing, Region of Interest (ROI) identification, handcrafted feature extraction, CNN-based classification, and separate Anthracnose detection were used as the experimental process.

To find the corresponding regions of the disease and produce annotated samples, the Image Labeler application was used for the detection experiment. The image acquisition conditions were also varied, and this was taken into account when interpreting the experimental results. Variations in light can affect the appearance of disease expression as well as the contrast, and background variation can create patterns that are not related to disease. The size of the leaf symptoms observed will vary with camera to leaf distance and the orientation of the leaves will change the spatial pattern. In evaluating the models, some of these natural variations were applied when the data was collected using different mobile devices and varied between different months. The dataset is still region-specific however, the observed robustness should not be interpreted as the overall robustness of all mangos growing regions or environmental conditions without further verification. Fig. 4 shows the Mango leaf photos with ROI labeling for disease-region annotation.

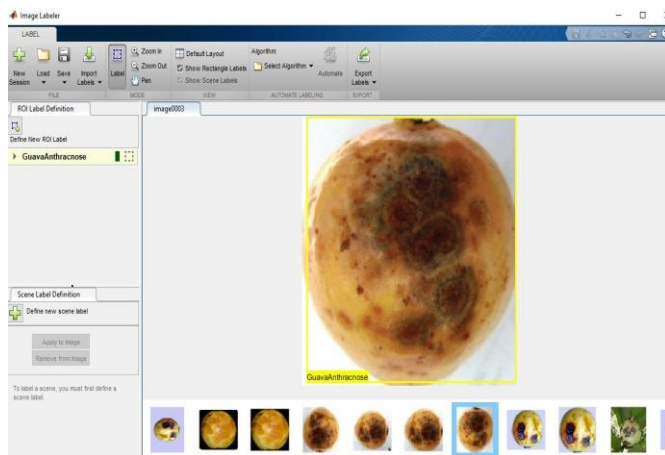


Fig. 4. Picture marking for ROI in Mango Pictures

Bounding boxes were applied to the target regions and positive samples were prepared for the cascade-detectors to be trained on, and negative samples were collected separately. The outputs of the framework were used to test its performance in detecting the locations of the disease within unseen images.

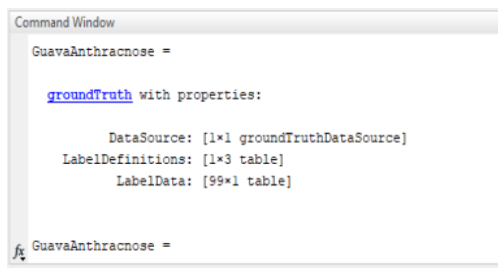


Fig. 5. Image labeler application output showing successful ROI selection

### B. Feature Extraction Performance (SURF, HOG, and LBP)

The accuracy of different handcrafted feature extraction methods, namely SURF, HOG and LBP were therefore examined to analyze their reliability on increasing image dataset complexity. The findings demonstrate that there were different performance patterns for the three feature extraction approaches with an increase in dataset complexity. SURF's performance on the feature extraction aspect was quite stable and did not degrade significantly with increasing complexity of the data sets and continued to extract interest points that were relevant. On the other hand, HOG was not a good performer on complex images but was in relatively good condition with low complex images, with high contrast. Among the evaluated techniques, LBP showed the least amount of behavior, with the number of features extracted decreasing significantly with the complexity of the images. The results reveal that SURF has shown stable feature extraction performance for the mango image database investigated when compared with HOG and LBP. The performance of the SURF, HOG, and LBP was compared in terms of the extraction function, as shown in the graph in Fig. 6.

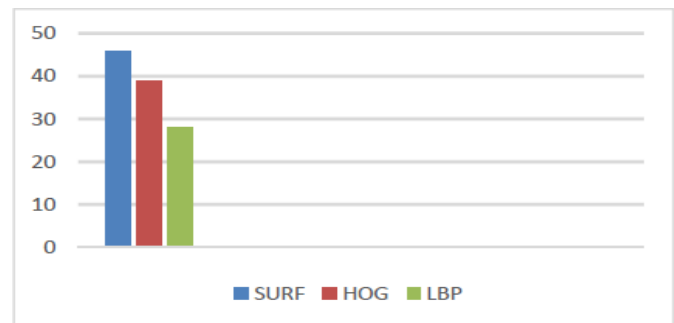


Fig. 6. Comparison graph showing SURF, HOG, and LBP performance

The handcrafted feature extraction experiments also revealed that the response of SURF was relatively stable as the number of complexities of the datasets increased, while HOG was more prone to performance degradation and LBP had more significant reduction in the number of feature features extracted. Results show that the handcrafted feature extraction methods evaluated in this work, such as SURF, are the most stable under the image conditions used in this study. The hand-crafted feature experiments were run independently from the CNN based transfer learning experiments, hence no fusion was performed between the SURF, HOG, LBP features and the ResNet-50 or Xception feature representation. From the methodological point of view the two sets of experiments complement one another: CNN models for disease classification and handcrafted descriptors for the feature-extraction behavior of the descriptors themselves.

### C. Comparative Analysis of Deep Learning Models

Transfer learning was used to test the classification capability of the core of the D-KAP framework for ResNet-50 and Xception models. Results of the performance metrics showed that ResNet-50 is a more appropriate network for this particular task. Table II shows the comparison of the models.

ResNet-50 achieved an accuracy of 80.0%, whereas Xception achieved 78.1%, a 1.9 percentage point difference. Even while ResNet-50 achieved the better accuracy, consideration should be used when interpreting the comparatively tiny difference. Since statistical significance tests and numerous independent training runs were not carried out in this research, statistical significance cannot be determined from the stated accuracy values alone. Therefore, rather than a clear advantage of ResNet-50, the observed difference can represent variance related to the dataset division, training procedure, and experimental circumstances. However, ResNet-50 performed somewhat better in classification than Xception under the experimental conditions taken advantage of in this study. To check whether the performance difference is statistically significant, future research should evaluate both architectures across several separate runs and provide mean performance, standard deviation, confidence intervals, as well as relevant statistical tests. Fig. 7 shows the performance graphs.

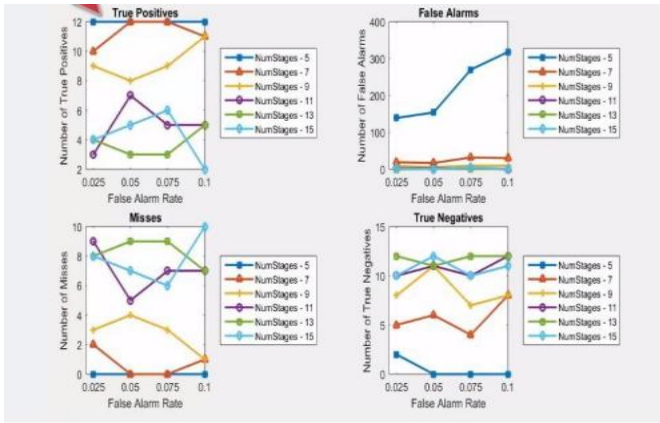


Fig. 7. Performance Graph

The Fig. 8 shows dataset is partitioned in training, testing, and validation the model.

| Total Data  | training | testing | validation |
|-------------|----------|---------|------------|
| 100%        | 75%      | 15%     | 10%        |
| 512         | 492      | 10      | 10         |
| 712, 1016.. |          |         |            |

Fig. 8. Dataset Partition for Training, Testing, and Validation

#### D. Detection and System Validation of Anthracnose

Apart from the multiclass classification experiments, a separate detection experiment was carried out for Mango Anthracnose using the trained cascade detector. Positive samples were created by using bounding-box coordinates

TABLE II  
PERFORMANCE COMPARISON OF CNN ARCHITECTURE

| Model Architecture | Classification Accuracy |
|--------------------|-------------------------|
| ResNet-50          | 80.0%                   |
| Xception           | 78.1%                   |

collected by the Image Labeler application and negative samples were created separately for detector training. The trained detector was then used to test images to detect Anthracnose regions and visualize the detected regions by drawing bounding boxes around them. When the samples were correctly labelled, the results reported showed a positive rate of about 90%. The framework successfully identified the anthracnose spots on a mango by drawing bounding boxes as shown in Fig. 9 and Fig. 10 respectively.

The detection system was then tested on a set of images not used during training, through an independent test procedure which was carried out by means of scripts made in MATLAB software; this procedure involved checking the number of correctly detected instances and the number of missed instances. The results are added as an extra visual-detection factor in the multiclass classification experiments performed with ResNet-50 and Xception.

The approximately 90% positive rate reported is based on correctly labeled positive samples whereas the independent validation process was performed to determine detection on images that were not included in the training set. Such a result should not be understood as a classification accuracy of the D-KAP multi-classifier but as the reported positive rate.

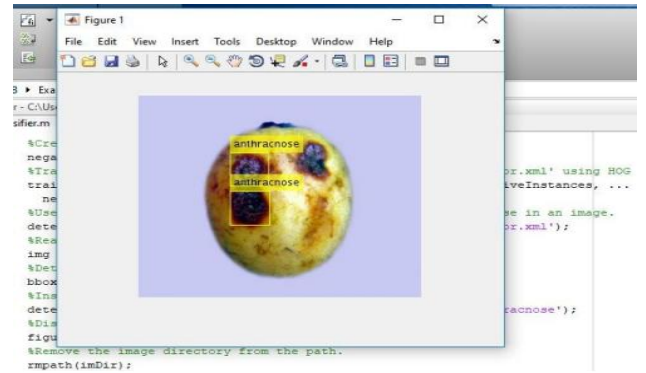


Fig. 9. Mango anthracnose disease detection results showing bounding boxes

The results also suggest that limitations of hardware might have influenced the potential performance of deep-learning experiments. Potential directions to improve model training and generalization are identified from the study, which involves leveraging more powerful GPUs and utilizing larger and more diverse datasets.

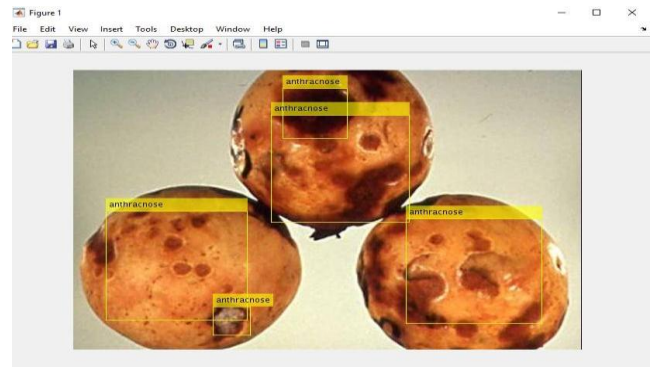


Fig. 10. Anthracnose spots on Mango successfully identified by the framework

This should therefore be viewed in the context of the relatively regional data set collected in Uch Sharif and the experimental resources employed in the study.

#### E. Practical Deployment Considerations

The proposed D-KAP framework can be practically adapted as a digital agricultural decision support system for farmers. A mobile app can be created where a farmer could take a picture of a mango leaf or upload an image to the app and the trained model would analyze the image and give the category of the disease. The experimental results presented in this work were carried out with a CNN structure that utilized transfer-learning, and hence, could be optimized and scaled down to be deployed in a mobile or edge device. The model can also be hosted on a cloud server with image processing and classification done remotely, and the farmer receives the prediction via a mobile or web application. This system could offer very hasty initial detection of a disease and a timely decision on the management of the crop. Further validation with larger and more diverse field datasets, optimization for computational and memory limitations, and testing under field conditions would be necessary for practical deployment. Hence, the present system should be regarded as a research prototype as well as a basis for creating an agricultural decision support application for field deployment, not as an agricultural field application.

#### V. CONCLUSION

This study developed the D-KAP framework for automated mango leaf disease analysis using deep learning, handcrafted feature extraction, and disease-region detection. A regional dataset of 419 mango leaf images was collected from Uch Sharif, Bahawalpur, including healthy leaves and leaves affected by Mango Scab, Mango Rot, and Alternaria leaf blotch. ResNet-50 and Xception, two of the evaluated CNN architectures, have accuracy rates of 80.0% and 78.1%, respectively. Even while ResNet-50 achieved more accuracy in the experimental setup, the 1.9 percentage-point difference is small, and the present single-run findings cannot be used to determine statistical significance. SURF also demonstrated comparatively more stable feature extraction behavior than HOG and LBP. In addition, a separate cascade-based Anthracnose detection experiment achieved an approximately 90% positive rate. The framework also offers foundations for future mobile, edge, or cloud-based agricultural decision-support applications, though further field testing and model optimization is required before implementation. Overall, the findings demonstrate the potential of the proposed framework for automated mango disease classification and detection.

#### VI. FUTURE WORK

The dataset will be expanded in future with images taken in other regions, varieties, seasons, lighting conditions, backgrounds, camera distances, and leaf orientations to evaluate and improve the robustness and generalizability of the models under a broader variety of field conditions. Other

methods for enhancing the classification performance include more powerful computational resources and advanced deep-learning and transfer-learning techniques. Moreover, it can be translated into a real-time mobile application in the field for disease detection. Light-weight edge deployment and cloud-based agricultural decision-support systems could also be explored as potential future implementations to enable farmers to receive accessible and timely disease identification. This deployment should be complemented with further field validation with images taken in various regions, mango varieties, seasons, light conditions, and camera devices. Large-scale mango disease monitoring using integration with UAV imagery, environmental sensors and hyperspectral data is also possible.

#### REFERENCES

- [1] S. N. Ghaiwat and P. Arora, "Detection and classification of plant leaf diseases using image processing techniques: A review," *Int. J. Recent Adv. Eng. Technol.*, 2014.
- [2] A. Camargo and J. S. Smith, "An image-processing based algorithm to automatically identify plant disease visual symptoms," *Biosyst. Eng.*, vol. 102, pp. 9–21, 2009.
- [3] A. Kadir, L. E. Nugroho, A. Susanto, and P. I. Santosa, "Leaf classification using shape, color, and texture features," pp. 225–230, 2013.
- [4] S. Arivazhagan and S. V. Ligi, "Mango leaf diseases identification using convolutional neural network," *Int. J. Pure Appl. Math.*, vol. 120, no. 6, pp. 11067–11079, 2018.
- [5] S. Arya and R. Singh, "A comparative study of CNN and AlexNet for detection of disease in potato and mango leaf," in *Proc. 2019 Int. Conf. Issues and Challenges in Intelligent Computing Techniques (ICICT)*, IEEE, vol. 1, pp. 1–6, 2019.
- [6] M. R. Mia, A. C. Chhoton, M. H. Mozumder, P. S. A. Hossain, and A. Hossain, "An approach for mango disease recognition using K-means clustering and SVM classifier," in *Proc. 2019 8th Int. Conf. System Modeling and Advancement in Research Trends (SMART)*, IEEE, pp. 404–409, 2019.
- [7] K. Trang, L. TonThat, N. G. M. Thao, and N. T. T. Thi, "Mango diseases identification by a deep residual network with contrast enhancement and transfer learning," in *Proc. 2019 IEEE Conf. Sustainable Utilization and Development in Engineering and Technologies (CSUDET)*, IEEE, pp. 138–142, 2019.
- [8] S. I. Ahmed, M. Ibrahim, M. Nadim, M. M. Rahman, M. M. Shejunti, T. Jabid, and M. S. Ali, "MangoLeafBD: A comprehensive image dataset to classify diseased and healthy mango fruits," *Data in Brief*, vol. 47, p. 108941, 2023.
- [9] G. S. Tumang, "Pests and diseases identification in mango using MATLAB," in *Proc. 2019 5th Int. Conf. Engineering, Applied Sciences and Technology (ICEAST)*, IEEE, pp. 1–4, 2019.
- [10] P. Veling, M. R. S. Kalelkar, M. L. V. Ajgaonkar, M. N. V. Mestry, and M. N. N. Gawade, "Mango disease detection by using image processing," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 7, no. 4, pp. 3717–3726, 2019.
- [11] M. R. Mia, S. Roy, S. K. Das, and M. A. Rahman, "Mango leaf disease recognition using neural network and support vector machine," *Iran J. Comput. Sci.*, vol. 3, pp. 185–193, 2020.
- [12] R. Gining, S. S. M. Fauzi, N. M. Yusoff, T. R. Razak, M. H. Ismail, N. A. Zaki, and F. Abdullah, "Harumanis mango leaf disease recognition system using image processing technique," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 23, no. 1, pp. 378–386, 2021.
- [13] S. Wongsila, P. Chantrasri, and P. Sureephong, "Machine learning algorithm development for detection of mango infected

- by anthracnose disease,” in Proc. 2021 Joint Int. Conf. Digital Arts, Media and Technology with ECTI Northern Section Conf. Electrical, Electronics, Computer and Telecommunication Engineering, IEEE, pp. 249–252, 2021.
- [14] M. Rahaman, M. R. Chowdhury, M. A. Rahman, H. Ahmed, M. M. Hossain, M. H. Rahman, M. S. Biswas, M. A. Kader, T. A. Noyan, and M. Biswas, “A deep learning-based smartphone application for detecting mango diseases and pesticide suggestions,” *Int. J. Comput. Digit. Syst.*, vol. 13, no. 1, pp. 1–1, 2023.
- [15] A. A. Salamai, “Enhancing mango disease diagnosis through eco-informatics: A deep learning approach,” *Ecol. Inform.*, vol. 77, p. 102216, 2023.
- [16] W. Sema, Y. Yayeh, and G. Andualem, “Automatic detection and classification of mango disease using convolutional neural network and histogram-oriented gradients,” 2023.