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Pomegranates Fruit Disease Classification Using EfficientNet Deep Learning Model

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Abstract

Pomegranate stands among the most important valuable fruits globally because it contributes significantly to food security and economic development throughout agricultural communities. The combination of diseases including alternaria alongside anthracnose bacterial blight and cercospora creates severe problems that lead to 75% yield reduction and deteriorated quality and substantial financial loss for growers. Manual inspections along with expert consultations currently fail to detect diseases effectively because they consume significant time while being subjective and their responses are usually delayed for managing the condition. The proposed research introduces the EfficientNet deep learning model for pomegranate disease classification because it exhibits high accuracy alongside efficient computing capabilities. A model based on the EfficientNet has been devised to classify disease affected fruits. The model was train and tested using Pomegranates fruits diseases dataset for deep learning model. The study's experimental results indicate that our proposed work attains an accuracy of 98.73%. The Proposed Solution functions as one of many agricultural technology developments through its deep learning system that delivers scalable accessible classification of pomegranate diseases while achieving high performance. Additionally the models proposed in this research can be now expanded to enable predict in real-time the quality of vegetable and fruits, by use of IoT devices. Moreover, the proposed model could be progressed into an android app where smartphone would enable farmers to take images of their plants or fruits in real time to receive instant classification reports related to plant or fruits disease.

Keywords: Machine Learning, Deep Learning, , Ensemble learning, Fruit Disease Detection , Pomegranates Disease Classification, Image Classification, EfficientNet, Smart Agriculture, Computer Vision

INTRODUCTION

Agriculture is a significant contributor to the economic growth of both developing countries and countries with a smaller population. Prior to the advent of the industrial revolution, agriculture was the primary source of employment for the vast majority of the human population. This is due to the fact that the majority of the population lives in areas that are governed by rulers and relies on cultivation for their survival (Bharate AA *et al.,* 2017). Among the wide range of food crops cultivated, fruits are regarded an essential source of vitamins, with good nutritional advantages (Gaikwad, S. A *et al.,* 2017). Pomegranate is among the most widely favored fruits and is rich in antioxidants and anti-inflammatory substances. Pomegranates are a high-value crop noted for their nutritional and medicinal benefits. They are primarily farmed in Mediterranean, Middle Eastern, and South Asian nations (A. S. Hussein *et al.,* 2023) (D. G. Maksudan *et al.,* 2023), (G. Benedetti *et al.,* 2023). Pomegranates are a profitable fruit crop that has a huge global profitable impact. The international market for pomegranates and their crops is forecast to rise in the future years, firm by the increasing demand for natural and nutritious meals.(Muhammad E.H. & Chowdhary *et al.,* 2021) Conferring to a report by Mordor Intelligence, the international pomegranate market was valued at USD 5.67 billion in 2020 and is likely to reach USD 8.46 billion by 2026, with a projected CAGR of 6.9% during the forecast period (Zhang, H *et al.,* 2022) This growth is being driven by the growing popularity of pomegranate nectar and other pomegranate-based products, as well as increased consumer knowledge of the health advantages of pomegranates. Despite its significance, research on disease detection and categorization in pomegranates is minimal compared to common crops such as tomatoes, wheat, and rice. (P. S. Mitkal *et al.,* 2023).However, pomegranate fruits are prone to being more susceptible to diseases, which causes huge losses in fruit production. Some noticeable pomegranate diseases include Alternaria, Bacterial Blight, Cercospora, and Anthracnose. These diseases reduce pomegranate productivity and crop, and reduce quality. For this reason, accurate detection of disease in early stages of occurrence is necessary. The majority of conventional disease detection strategies in fruits are based upon physical intervention, requiring labor intensive, time wasting, and prone to human error (Iqbal, Z. *et al,*. 2018).

Advanced machine learning and computer vision based techniques can make these disease detection and classification problems scalable. Using deep learning (DL) techniques, several studies have proposed fruit disease classification using fruit features and patterns (Syed-Ab-Rahman *et al.,* 2022). Concurrently, Convolutional Neural Networks (CNN) based models have gained popularity in the agriculture domain especially for fruit disease detection (Alharbi, A. G. Arif, 2020) which can quickly and accurately analyze a large number of fruit images and have helped automate the fruit disease classification process (Naranjo-Torres, *et al.,* 2020).However, traditional conventional CNN models primarily focus on spatial features in images and overlook the temporal dimension of disease progression. In addition, the performance of the CNN model can be affected by low image quality. To address this limitation, this study is to create a precise and effective model that can identify common pomegranate diseases from images of fruit.

Pomegranates are grown in several regions of Pakistan, primarily in areas with a favorable climate for cultivation. Pomegranates thrive in dry, hot climates with well-drained soils. Pomegranates from Pakistan are prized for their flavor, vibrant color, and juiciness. Baluchistan, in particular, is known for producing high-quality varieties such as sweet red pomegranates (Muhammad Nafees *et al.,* 2015). It is crucial to categorize fruits into normal and disease-affected post-harvest for marketing and exporting purposes. The human classification of fruits is ineffective due to inaccuracies and time consumption. Pomegranates are susceptible to various diseases, including Bacterial Blight, Anthracnose, Cercospora fruit spot, and Heart Rot. Agriculturists possess fundamental knowledge regarding these diseases; however, more precise methodologies are necessary to differentiate between healthy and diseased fruits for optimal export quality.(Mutegeki R *et al.,* 2020). Recent years have seen extensive research on the detection of diseases in various fruits and plant parts, such as leaves, utilizing image processing techniques. However, insufficient research has been conducted to identify and classify diseases in pomegranate fruits. Numerous studies have been focused on identifying diseases and classifying pomegranates fruits by reducing losses and increasing the output. In the study by (Pawar *et al.,* 2017), an ANN based method for segmentation of disease on pomegranate was used with an accuracy of up to 91%. This investigation utilized a feature extraction process to extract features from fruit parts infected with the bacteria. It is shown that with the proposed approach, a classification accuracy of 90% was achieved.

Problem Statement

Currently, the methods for detecting and classifying diseases largely rely on human examination, a process that is time-consuming, susceptible to mistakes, and requires specialized expertise that many small-scale farmers frequently want. It is crucial to categorize fruits into normal and disease-affected post-harvest for marketing and exporting purposes. The human classification of fruits is ineffective due to inaccuracies and time consumption Furthermore, the early signs of these conditions frequently go unnoticed, leading to delays in timely intervention and a heightened reliance on broad-spectrum pesticides, which can pose risks to both environmental integrity and human well-being. (G. Benedetti *et al.,* 2023).

While the use of machine learning and deep learning models in agriculture is on the rise, there remains a scarcity of studies focused on the implementation of advanced architectures like EfficientNet for classifying and detecting diseases in pomegranate plants. Deep learning has been utilized in significant agricultural crops such as wheat, rice, and tomatoes (P. S. Mitkal *et al.,* 2023). The classification of pomegranate diseases is still a relatively unexplored area, highlighting a notable gap in current studies. The objective of this study is to create a precise and effective model capable of classifying prevalent pomegranate diseases based on images of the fruit. This solution offers farmers an economical and easily accessible method for detecting diseases, facilitating swift action to minimize crop losses and encourage sustainable agricultural practices through focused disease management.

The process of obtaining input data from cameras or scanners is the first step in any CV model. This step is essential to the CV model. When it comes to image acquisition systems, the selection of the image-capturing sensor, the lighting conditions, and the specific portion of the electromagnetic spectrum being examined stand out as the key elements that significantly influence the outcome (Mishra *et al.,* 2017). A wide array of specialized imaging sensors is at your fingertips, including X-ray cameras, visible light cameras, and multispectral cameras. The image acquisition model must be capable of adapting to various lighting conditions. A system designed to monitor products in the external environment necessitates supplementary software that facilitates the use of a classification model, allowing for effective generalization across various lighting conditions.

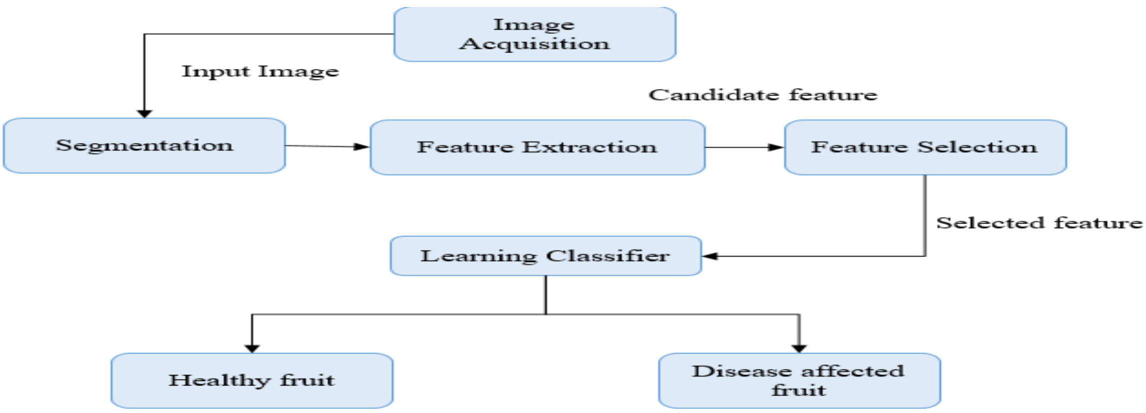

Figure 1.
Process involved in automated fruit disease detection and classification

Image Pre-processing

Along with getting the image, we also use some pre-processing techniques to improve the quality of the captured image (L. Chen *et al.,* 2012). These techniques involve pointing out key features or getting rid of any noise in the image. Image scaling and image blurring are two ways to remove noise, both focusing on minimizing the effect of pixels that stand out too much from their neighbors. After this step, we apply image sharpening to enhance the clarity of the edges in the images (G. Ying *et al.,* 2009). The color space you choose really affects how well you can identify features accurately. There are three levels that make up the image pre-processing technique: low-level processing, medium-level processing, and high-level processing. The first level of processing involves tasks like modifying grayscale images, enhancing contrast, and getting rid of noise. Using geometric transformation, they can create a new image that looks better or change where the main object in the image is located. The second level of processing covers the segmentation, description, and classification of the objects found in the image. This process creates a bunch of contours or regions. The areas needed to figure out the sequence of features that create the Region of Interest (ROI) are set by filtering those features (Wang Z *et al.,* 2014). The ellipse parameter is a handy way to figure out both the orientation and the size of the area. The bounding boxes help figure out the height and width of the ROI.

Segmentation

The main purpose is to divide the image into various regions that exhibit a strong relationship with the objects located within the region of interest (ROI) (Brosnan, T *et al.,* 2004). This technique helps us identify the affected regions shown in the image of the fruit. When it comes to segmentation, there are three main types you'll often come across: thresholding, edge-based, and region-based segmentation. Thresholding is actually a pretty straightforward approach when we're talking about segmentation. Thresholding is used to create binary images from grayscale images. It's a fast process that doesn't need any extra pre-processing, and the edge-based segmentation helps spot any irregularities in the grayscale level, color, or surface of the pixels. Finally, region-based segmentation sorts the pixels that are similar to each other, which helps to identify a specific object in the image. Background subtraction is a popular method for segmenting regions, and it's used quite a bit. This technique helps to spot the objects that stand out in the image against the background.

Feature extraction

A descriptor can be used to represent features in computer vision. This descriptor is all about capturing the essence of image details, representing every measurable property you can think of. This abstraction aims to identify a few key criteria found in the image or specific areas of it (Gutierrez-Osuna & Hierlemann., 2010). So, in this case, we're talking about fruit, and the details we pulled from the image show things like its color, texture, and shape. Histograms and the statistical moments like mean, variance, and skewness of a feature value for each pixel in a region of interest (ROI) are great examples of how we can use statistical methods to summarize data. There are several stages of granularity that help us figure out these "region features." Interestingly, it's the least probable granularity that ends up defining the features of the whole image. Usually, a super pixel comes from breaking down the image into smaller segments and treating each of those little pieces as a region. We're doing this process to create a super pixel. A single pixel is usually the tiniest area that we can think of as possible.

Feature Selection

The dataset had more features than what we used in the classification process. That's why it's essential to figure out how we can reduce the number of features needed for classification. There are several different feature reduction models out there that you can use. These models work in one of two ways: they can either pick a subset of features from a big set or use Principal Component Analysis (PCA) to create a smaller set made up of mathematical functions of the original features. There are several FS techniques you can use to compare individual features, helping you pick the most beneficial ones or get rid of the less useful ones for classification. One example of this is Sequential Forward Selection (SFS), which begins with an empty set of features. Next up, we use a greedy searching technique to pick out the relevant features that we want to add to the classifier. This process goes on until we either reach a set number of features or adding more features stops improving the classifier's results.

Classification

In the realm of machine learning, classification is basically an algorithmic process where you take a data point and assign it to a set of class labels. So, when we talk about fruit, we often use "normal" to refer to the healthy ones, and "abnormal" for those that are disease infected. A data point, often called an instance, consists of a bunch of feature vectors that hold all the info related to the classification process. The classification process using machine learning is supervised. This means that the model is mainly trained on data points that a human has already evaluated and given specific performance feedback on. To make a classification decision for a new set of data, the classification model needs to figure out the relationship between the provided results and the data's characteristics.

OVERVIEW OF MACHINE LEARNING AND DEEP LEARNING

Overview of Machine Learning

Machine Learning is a subset of the Artificial Intelligence which is used to develop the system that learn automatically from the data without being explicit programmed. (Jaime *et al.,* 1983). Machine learning is used these days for all sorts of commercial purposes like suggesting products to a consumer based on their purchase history, predicting the market stock fluctuations, and translating the language from one to another. Today, in popular language, “Machine Learning” and “Artificial Intelligence” are frequently used terms due to machine learning being used in AI for most parts in our world. Even so, the two adjectives are useful differently. When we say AI something in general in an attempt to create machines that capable of human-like intelligence, but machine learning it is the application of machine learning algorithms and data sets to achieve such. Machine learning exists in three categories according to the learning system employed: supervised learning and unsupervised learning with semi-supervised learning as the third category.(S. Chowdhury *et al.,* 2020). Supervised learning techniques analyze pre-labeled information collections which includes clear final results identification. This method operates with data that does not contain any predetermined labels. Unguided learning allows researchers to perform initial data investigations through clustering methods. People usually use visual analytical methods to represent unsupervised technique results. The semi-supervised method unifies supervised learning techniques with those of unsupervised learning. These techniques apply to situations where the information lacks predetermined tags. A semi-supervised method analyzes data where only some of the entries lack labels.

Overview of Deep Learning

The DL is composed by a sets of ML models that map the high-level abstraction within the data in a series of EVT. It relies on the artificial neural network (ANN), whereby the combined model always uses the learning model and incrementally expands the data volume up to the training process is optimized. . A Model is not efficient unless it can support large volume of data. It is said to be training process in which the number of layers in neural network (NN) is growing with time DL research models (S. Sunitha., 2021).Deep learning models enable to model and understand complex process of perception with good accuracy. It is also referred as deep, structured and hierarchical learning with many layer of nonlinear processing unit for rephrase and feature extraction. The input to the previous layer is now an input to the incoming layer. And so it goes on with all layers.

Deep Learning Vs Machine Learning

A deep learning structural model made into several hidden layer and so many neuron within one layer. The hierarchical structure is well adapted to represent the data in hierarchically growing abstractions. Fig.1.4 showing the difference ML and DL and models (R.Sujatha et al., 2021).

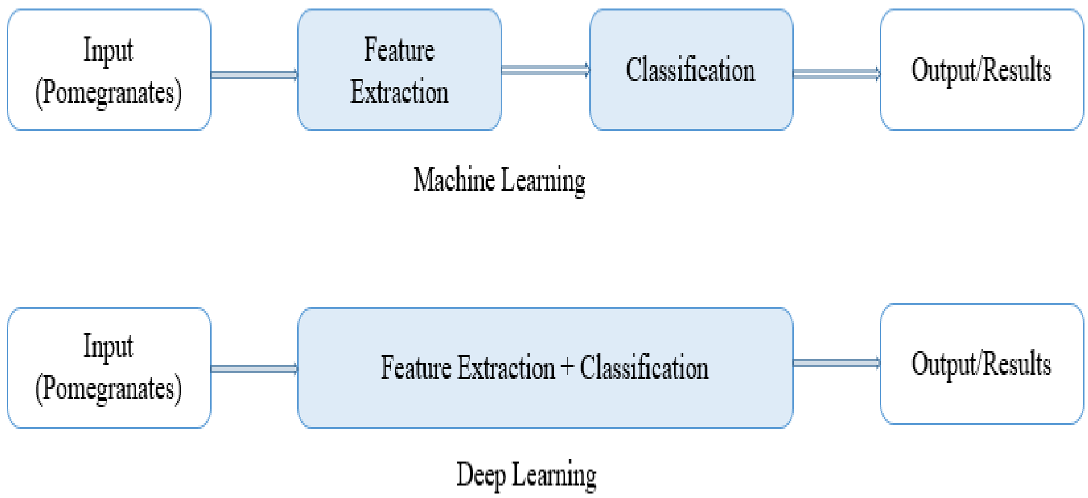

Figure 1.
Difference b/w machine learning and deep learning

Pomegranates Fruits Disease Detection

Pomegranate stands among the most important valuable fruits globally because it contributes significantly to food security and economic development throughout agricultural communities. The tree of pomegrantes (Punica granatum L) species grow as ancient and fleshy deciduous fruits producers within tropical and subtropical regions. It is part of the Lythraceae family, there are two species; P. protopunica and P. granatum (Pablo Melgarejo *et al.,* 2020). Later, pomegranates were considered the mother of Punica species. The tree of pomegranate with long height 6-10 cm, and expand a lot of thorny branches. (Hatib *et al.,* 2009).

Figure 2.
A view of pomegranate tree

Fig. 1.3 shows, a pomegranate tree (Kahrmanoglu *et al.,* 2016), produces its fruit. Harvest of the fruit is at the mature stage. The mature fruits are related to the color of rind. The edible fruits are round in shape with a diameter of aboutruptions 5–12 cm and have a thick reddish exozyme. The pomegranate skin is far too thick for consumption with approximately 100 edible seeds of the skin called arterlies. Each segment of the whole fruit contains tender arils that belong to the edible part.

1.8.1 Occurrence

Pomegranate, native to Iran and adjacent areas, is commercially cultivated in China, Iraq, Myanmar, Afghanistan, Russia, India, Spain, Pakistan, and Japan (Mars, M., 1996). Pomegranates are grown in several regions of Pakistan, primarily in areas with a favorable climate for cultivation. Pomegranates thrive in dry, hot climates with well-drained soils. Pomegranates from Pakistan are prized for their flavor, vibrant color, and juiciness. The primary states for pomegranate cultivation in Pakistan include Baluchistan, Punjab, Sindh, Khyber Pakhtunkhwa (Muhammad Nafees *et al.,* 2015). Pomegranate is characterized as the "Fruit of Paradise." The areas dedicated to pomegranate cultivation are expanding worldwide due to its adaptability, drought resistance, higher yield, resilience, exceptional preservative qualities, and competitive pricing in both domestic and international markets. It flourishes more effectively in arid, cold, and hot climates.

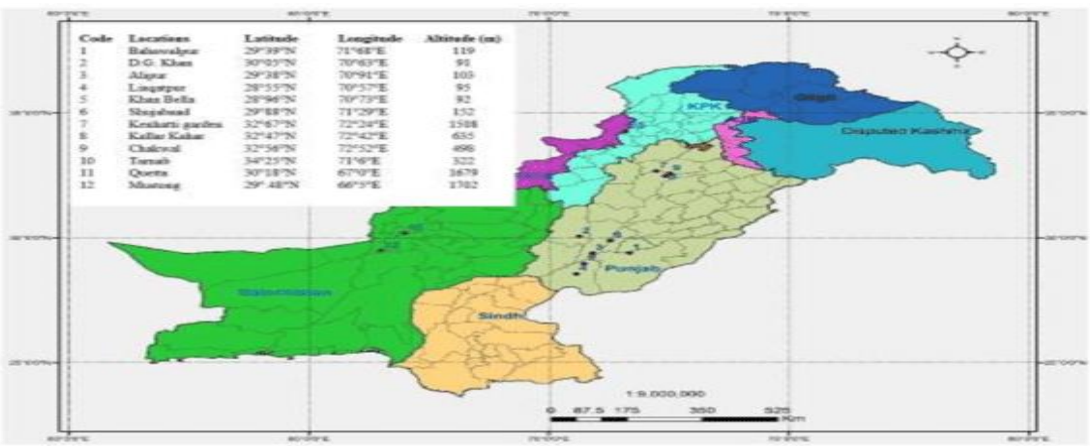

Figure 3.
Pomegranate cultivating regions in Pakistan

(Source: https://www. https://www.pakjas.com.pk) illustrates the cultivation areas of pomegranate in Pakistan.

Nutritional Benefits

Pomegranates are esteemed for their flavor and nutritional value. It possess an acidity of 7-8% and are employed in the production of 'anardana'. The edible portion 'arils' of the fruit contains 1.6% protein, 5% fiber, 16-18% carbohydrates (sugars), and 78% water. Each 100 grams of fruit contains approximately 10 mg of calcium, 70 mg of phosphorus, and sufficient quantities of iron, riboflavin, and antioxidant vitamins C and E and the juice is invigorating and possesses considerable medicinal value (Ghadge *et al.,* 2015). While the different components of the Pomegranate plants are beneficial in treating numerous ailments. The shoot bark is employed for weight loss in the body. The peels of fruits are employed to manage diarrhea, dysentery, and for intestinal deworming. Wines are produced from sugary liquids. The antioxidant properties of pomegranates provide protection against tumors, cardiovascular diseases, and cognitive disorders (Ropaki *et al.,* 2013). It possesses anti-inflammatory properties that protect against tumors and other chronic diseases.

Pomegranates Diseases

Pomegranate production faces numerous challenges from biotic and abiotic factors, including diseases and pests (Karen Munhuweyi *et al.,* 2016). The primary factors contributing to the reduced cultivation and production of pomegranate crops encompass the deficiency of suitable varieties, unpredictable climatic fluctuations, inadequate irrigation infrastructure, nutritional deficiencies, diseases, pests, postharvest losses, improper storage, insufficient marketing and promotion, and cost variability. (Munhuweyi *et al.,* 2016).Diseases such as fruit cracking, wilt, sunscald, bacterial blight, pests, and damage caused by trips and fruit borers represent significant biotic and abiotic stresses associated with pomegranate production. Researchers have found that microbial diseases, like "bacterial blight" or "oily spot disease," caused by Xanthomonas, axonopodis, punicae, are the main thing that halts pomegranates from being grown. The disease impacts various parts of plants, including the fruit, stem, branches, and leaves. Common diseases affecting pomegranate fruit include anthracnose, Cercospora, bacterial blight, and alternaria. Figure 1.5 illustrates the symptoms of the aforementioned diseases.

Figure 3.
Types of pomegranates disease

Alternaria

One of the most common diseases that can affect pomegranate fruits. The disease manifests itself on the surface of the fruit as a series of small, circular spots that are brown or black in color. It's possible that these spots have a dark border and a slight depression in the middle (Gk, Ravichandra. *et al.,* 2023).

Anthraconose

This disease (Krishpa *et al.,* 2015) manifests symptoms such as consistent or inconsistent spots on leaves, the calyx of the fruit, and the fruit's rind. These areas subsequently transform into dark brown, deeper cavities.

Bacterial Blight

The prevalent symptoms of this disease (Icoz-Sulu *et al.,* 2014) include a few to numerous dark-colored, non-uniform spots that may manifest on the leaves or rind of the fruit, resulting in significant defoliation. The infection disseminates to the branches and stems, resulting in the splitting of the shoot. In advanced stages, the spots develop a deep brown color, becoming elevated and oily, and fissure with L-shaped splits.

Cercospora

The predominant symptoms of Cercospora consist of dark brown lesions on leaves or fruits that initially appear circular and subsequently become irregular as they enlarge (P. S. Mitkal *et al.,* 2023). The apertures on the leaves are dark, blackish, and exhibit profound lesions. The bacterial spots on the fruits are darker and vary in size. The fruit's rind is devoid of cracks and stickiness. The branches of the Cercospora-infected tree exhibit lesions that ultimately lead to desiccation. In severe instances, leaves become yellow, and significant defoliation occurs.

Healthy

Reflecting appropriate cultivation and handling, healthy pomegranates are firm, vivid in color, free of blemishes or signs of disease. Their delicious, nutrient-dense arils accentuate their superior quality and health advantages. (Arun Kumar R *et al.,* 2021).

LITRATURE REVIEW

Review Of Fruit Disease Diagnosis Model

A study was conducted by (M.T. Vasumathi *et al.*, 2021), where pomegranate fruits were classified into normal and abnormal categories using a hybrid CNN-LSTM model. The Dragonfly algorithm was employed to enhance the model via the classification process. Pomegranates face various diseases, such as anthracnose, bacterial blight, cercospora, and heart rot, even though they are greatly esteemed for their medicinal benefits. By employing attributes like color, texture, and shape, the study aims to facilitate the early detection of these diseases. The images were acquired from Kaggle and subsequently underwent preprocessing using techniques like Principal Component Analysis and MapReduce. As a result, the application of Dragonfly led to a rise in classification accuracy to 97.1%. (Aisha Naseer *et al.,* 2024) demonstrate the detection of pomegranate growth stages using a novel transfer learning approach and image data collection.

A random forest model was trained to accept a set of probabilistic special features derived from image spatial features collected through a novel method developed by the researchers. This methodology utilizes a dataset comprising 5857 images, which have been classified into five distinct categories: bud, early fruit, flower, mid-growth, and ripe. This method achieved an impressive accuracy of 98%, outperforming the leading techniques available today. This study discusses several potential applications of the method. These applications aim to support farmers in optimizing crop production and mitigating risks linked to diseases and pest invasions. Use of deep learning models (Wei, Kaihu *et al.,* 2022) investigates the application of the models for disease classification in agriculture. This study consisted in the conduct of three experiments focused on the VGG, GoogLeNet and ResNet models. In addition, an attention module was embedded into ResNet for the enhanced feature extraction. The results of experiments show that, the model combined with the interaction module (ResNet-CBAM) obtain the highest accuracy rate. Moreover, they analyzed three deep learning interpretability approaches: SmoothGrad, LIME and GradCAM final result for them was GradCAM was the best methodology for applications in agriculture.

To increase the agriculture productivity (Muzammil Khan *et al.,* 2024) presented a neural network based model to diagnose early and late blight diseases in tomato plant. The model that were built was based on Inception V3 architecture but trained on the Plant Village dataset with 6000 images of tomato leafs. On the basis of the model, on a classified accuracy of 97.44% was got. This work achieves a non-destructive, accurate and inexpensive method for disease detection by deep learning technology, which may raise the demand of tomatoes and be able to promote the development of the industry. (Syed Ab Rahman *et al.,* 2021) implements a deep convolutional neural network (CNN) which involves a two stage approach to detect and classify citrus diseases by using images of leaf tissue. A Region Proposal Network (RPN) is included in the network to generate regions, and they are classified by regions based on specifically disease categories using classifier. The main area of focus on the still ongoing investigation into citrus disease brought out involves Huanglongbing, citrus black spot and citrus bacterial canker. The suggested model attained detection accuracy of 94.37%; and average precision of 95.8% shot seen, signifying fulfilling disease image detection as well as early accurate detection. This instrument was designed to give a trustworthy approach for farmers in identifying and managing citrus diseases. This tool is designed to prevent against crop losses and improve agricultural yields. (Zahid Iqbal *et al.,* 2018) carry out an extensive review of various automated detection and classification techniques for the diagnosis of citrus plant diseases by image processing methods. The paper points out that in order to get a more accurate detection well-established deep learning techniques and tricks are required. As a consequence, automated methods, although they hold great promise, to achieve final automation of the detection and classification tasks, even more work is required.

Review Of Existing Pomegrantes Fruit Disease Detection Techniques

By observing the fruit from the outside it is possible to tell if a fruit is diseased by looking at it from the outside. It is possible to tell whether a fruit is normal or abnormal by looking at its external characteristics, such as its color, the presence of lesions or black spots, its weight, its shape, and the plant stand itself. This is especially true for pomegranates.

A segmentation model for detecting pomegranate fruit diseases was presented using a K-means clustering-based technique, as detailed by (Lamini S.B. Ravikumar., 2018) Furthermore, a variety of machine learning models, such as PNN, KNN (K-Nearest Neighbors), and SVM classifiers, are employed to accurately designate the suitable class label. In the context of pomegranate disease detection, a new classification model was developed by (Pooja Kantale & Thakate., 2020). The model being presented integrates both the particle swarm optimization (PSO) algorithm for feature selection and the AdaBoost model for the classification process. The study conducted by (Lamini & S.B. Ravikumar., 2018) introduced a novel classification model aimed at detecting diseases in pomegranate fruit. Initially, it enables the capture and upload of images to the system, which subsequently performs an image segmentation process utilizing fuzzy c-means clustering. The subsequent step involves the utilization of PNN, SVM, and KNN models as classification tools to determine the suitable class labels. (Chakali, R., 2020) developed a CNN model aimed at detecting pomegranate fruit and plant leaf disease. The model has reached an impressive score of one hundred percent in classifying a good fruit and has demonstrated an accuracy of 85.71 percent in detecting bacterial blight disease. In another study conducted by (Bhange *et al.,* 2015) to identify diseases in pomegranates using CNN, the model was provided with an input of sixty images. The model demonstrated an accuracy of 88% in identifying healthy fruit, whereas its accuracy in identifying infected fruit was 79%. A technique involving artificial neural networks (ANN) was employed by (Tripathi. Maktedar *et al.,* 2016) to identify bacterial blight disease in pomegranate fruit. Their efforts yielded a commendable accuracy rate of 90%. AdaBoost Ensemble Classifier as studied by (Kantale *et al.,* 2020) has been made use of in the classification of diseases in pomegranate plants. Three diseases created and classified: bacterial blight, antracnosa rot of the fruit and antracnosa. The AdaBoost classifier needs 14.15 seconds for data processing in the training phase. The AdaBoost classifier obtained a classification accuracy of 92,9% with a sensitivity of 90.6% and a f-score of 89,83%. In their research, (Jayashri et al., 2021) looked at the diseases diagnosis in pomegranate fruit through image processing techniques and classifier. In disease detection and classification, ANN fairly accomplishes good accuracy rate of 92.65%.

Research Contributions

Pomegranates are grown in several regions of Pakistan, primarily in areas with a favorable climate for cultivation. Pomegranates thrive in dry, hot climates with well-drained soils. Pomegranates from Pakistan are prized for their flavor, vibrant color, and juiciness. Baluchistan, in particular, is known for producing high-quality varieties such as sweet red pomegranates (Muhammad Nafees *et al.,* 2015). It is crucial to categorize fruits into normal and disease-affected post-harvest for marketing and exporting purposes. The human classification of fruits is ineffective due to inaccuracies and time consumption. Pomegranates are susceptible to various diseases, including Bacterial Blight, Anthracnose, Cercospora fruit spot, and Heart Rot. Agriculturists possess fundamental knowledge regarding these diseases; however, more precise methodologies are necessary to differentiate between healthy and diseased fruits for optimal export quality.

A proposed machine-based system employs a EfficientNet model to train computers for classifying fruits as either Healthy or disease affected (Mutegeki R *et al.,* 2020). Recent years have seen extensive research on the detection of diseases in various fruits and plant parts, such as leaves, utilizing image processing techniques. However, insufficient research has been conducted to identify and classify diseases in pomegranate fruits. Firstly the research conducted on disease identification and classification of fruits has focused on a restricted dataset, comprising between 60 and 120 images. Secondly, the number of epochs required for convergence in existing algorithms is substantial, with some cases reaching up to 10,000. This research work focuses on the design of Efficient Net DL models for pomegranate fruit disease classification. This research work is divided into a set of three research objectives as listed below.

- To perform a thorough analysis of various ML and DL-enabled models for detecting plant disease, fruit disease, and pomegranate fruit disease.

- To design a pomegranate fruits disease classification model using the Efficient Net deep learning model that can classify these diseases with high accuracy and efficiency.
- In order to validate the performance of the proposed deep learning-based pomegranate fruit disease diagnosis models on our dataset and to investigate the results in terms of different methods of performance evaluation.

METHODOLOGY

Dataset Discription

The dataset contains five thousand nine hundred and ninety-nine images of pomegranate fruit that have been labeled and categorized into the following five categories: healthy, bacterial blight, anthracnose, alternaria, and cercospora. This dataset is available for download from Mendeley Data, which can be found at https://data.mendeley.com. The only fruit that is included in this dataset is a single fruit that is displayed on a plain background with the class name labeled. Multiple authors of research projects made use of this dataset as a result.

Table 1.
Data set Description

Sl. No.	Particulars	Description		
		Images count	Dimension	Resolution
1	Healthy	1450	(3120 × 3120)	2200 dpi
2	Bacterial blight	966	(3120 × 3120)	2200 dpi
3	Anthracnose	1166	(3120 × 3120)	2200 dpi
4	Cercospora	631	(3120 × 3120)	2200 dpi
5	Alternaria	886	(3120 × 3120)	2200 dpi
Total		5099		

The compilation of pomegranate fruit disease dataset aims to promote knowledge and innovation in pomegranate, especially about the identification and control of diseases. With machine learning, particularly deep learning, the dataset provides great advancements to agriculture, plant pathology, and data science. The process of creation entails careful gathering of images, detailed annotation, and systematic classification, highlighting the variety in disease presentations. This standardized dataset promotes collaboration, aids in the development of advanced algorithms, and seeks to improve disease resistance and cultivation practices in pomegranate farming. This standalone data article serves as a crucial resource for benchmarking and validating algorithms, enhancing the collective knowledge in the field and supporting both ongoing and future studies in the identification and management of pomegranate fruit diseases.

Preprocessing

In any deep learning process, data preprocessing is the initial stage where images are converted into a compatible format. Conversely, it renders the images readily interpretable by the algorithm. The implementation of EfficientNet techniques does not necessitate extensive image pre-processing; however, fundamental pre-processing is conducted to enable Efficient Net to extract features more effectively and accurately.

Feature Extraction

The most difficult aspect of recognizing fruit patterns is discerning harmful and distinctive characteristics of the fruit. The number of fruit spots, fruit shape, and fruit color are the essential features necessary for identifying a diseased fruit, which are extracted and utilized for training purposes. Feature extraction is a method employed to preprocess data, enhancing model performance beyond a baseline for standard classification datasets.Using ResNet-50 as a feature extractor and leveraging the pre-trained features for the proposed Efficient Net architecture could lead to better performance and better use of computing resources.

Classification

Pomegranate is vulnerable to various diseases that can negatively impact both the quality of the fruit and its overall yield. A diverse group of agricultural experts, growers, and pomegranates cultivators have individually confirmed these diseases using images of pomegranates fruit. The dataset related to pomegranate fruit diseases is utilized to develop a model designed for the classification of pomegranate fruits. Individuals with little to no knowledge of pomegranates will still be capable of recognizing fruit affected by disease through the current model. Key characteristics for classifying fruits have been determined, the dataset has been trained with these features, and ultimately, successful fruit classification has been accomplished.

Classification Environment

Deep learning techniques have proven effective in classification. The present study intends to employ advanced deep learning techniques to effectively classify pomegranate diseases.

Library

Deep learning model training requires multiple essential libraries. TensorFlow, keras, matplotlib, OS, and time were among the necessary libraries that were used. These libraries perform various functions essential for deep learning model creation and analysis.

Tensor Flow

Google's TensorFlow is a good deep learning framework that makes deep learning model creation, training, deployment easier. TensorFlow makes it easier to construct and test models by enabling the representation of mathematical operations in a computation graph.

Keras

A high-level deep learning toolkit and API called Keras was created by Google. It used independently or in combination with other deep learning frameworks like TensorFlow, Microsoft Cognitive Toolkit, or Theano. It offers a simple user interface that compresses the difficulties of low-level neural networks, making deep learning model development and experimentation easy and efficient.

Matplotlib

Matplotlib is a python library toolkit for creating best plots, graphs and charts for data analysis, research, and engineering applications. It is compatible with NumPy, a Python numerical computing library.

OS

The python os module includes functions to interact with the operating system, allow for a number of OS-related functionality and gathering of information.

Sklearn

Scikit-learn is a comprehensive state-of-the-art machine learning library in Python is powerful user-friendly which is useful primarily in Automobile industry, but also in several other domains. devices for statistical modelling as well as machine learning. This tool works very simply with other python libraries like NumPy, and Pandas, data preprocessing, model selection, and evaluation performance of a number of machine learning methods.

Efficientnet Model

The EfficientNet system is composed of a series of convolutional neural networks (CNNs), created particularly for image classification (Mingxing Tan 1 Quoc V. Le 1., 2020). In order to achieve the best balance of model accuracy and the required computation resources, the EfficientNet uses a compound scaling strategy.

Compound Scaling

The author of the EfficientNet mentioned that cost function is actually a mapping of various scaling dimension such as depth, width, and image size get intertwined. High-resolution images require more intricate networks to capture a wide range of features with greater pixel density (Mingxing Tan 1 Quoc V. Le 1., 2020). Also, having a wider network is very important to be able to catch all the small details in these high definition images. In order to be accurate and efficient, it is required that all the components of the network width, depth, and resolution are scaled up the convolutional neural network. However increasing the scaling of CNNs by particular coefficients results in better outcomes. Compound scaling means adjusting on or more dimensions or factors simultaneously to achieve top performance or efficiency.

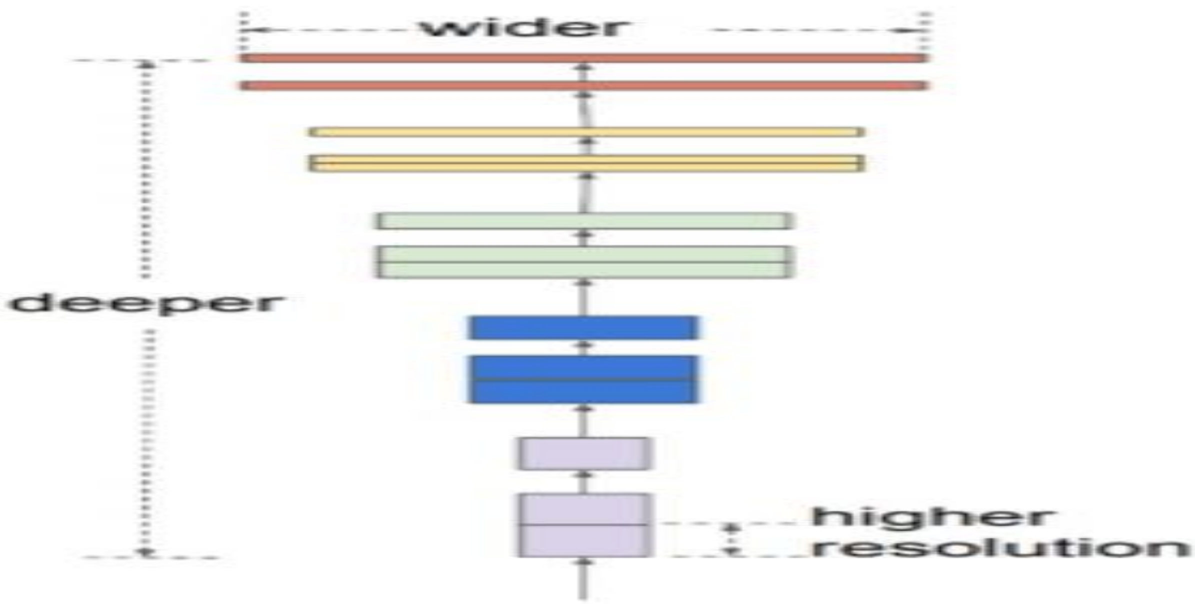

Figure1.
Compound Scaling

The compound scaling coefficient method scales all three dimensions, depth, width, and resolution, proportionally according to a specified compound coefficient ϕ.

The mathematical expression for the compound scaling method is as follows:

$$\begin{aligned} \text{depth: } & d = \alpha^{\phi} \\ \text{width: } & w = \beta^{\phi} \\ \text{resolution: } & r = \gamma^{\phi} \\ \text{s.t. } & \alpha \cdot \beta^{2} \cdot \gamma^{2} \approx 2 \\ & \alpha \geq 1, \beta \geq 1, \gamma \geq 1 \end{aligned}$$

α: Scaling factor for network depth (typically between 1 and 2)
β: Scaling factor for network width (typically between 1 and 2)
γ: Scaling factor for image resolution (typically between 1 and 1.5)
ϕ (phi): Compound coefficient (positive integer) that controls the overall scaling factor.

This equation shows us how to adjust the model depth, width, and resolution for the best performance possible.

Efficient net Architecture

EfficientNet-B0 model which has been discovered through Neural Architectural Search (NAS) takes the place of the baseline model (Tashin Ahmad & Noor Hossain.et al., 2021). Below are the major parts of the architecture:

- MBConv block (Mobile Inverted Bottleneck Convolution)
- Squeeze-and-excitation optimization

MBConv block (Mobile Inverted Bottleneck Convolution)

The MobileNetv2-inspired MBConv block is an advanced inverted residual block.

Residual Network

Residual networks is a deep convolutional neural network architecture which is proposed to deal with the vanishing gradient issue which occurs when the network depth goes deeper, so the gradient goes down. ResNets solve this problem to allow the training of very deep networks. This layer aids the flow of gradients in the network by blending the initial input with the output of the transformation via Kaiming He et al.(2015).

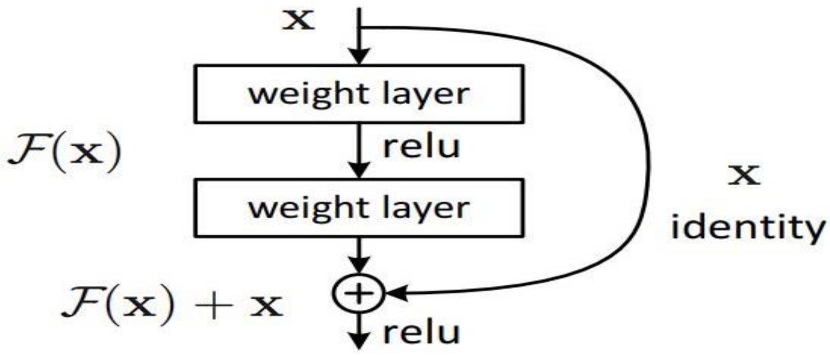

Figure 2.
Compound scaling expression

Inverted Residual Block

The primary structure in residual blocks utilized in ResNets consists of convolutions that simplify the input feature map. The initial input is subsequently incorporated into the output of this convolutional pathway through a shortcut or residual connection. This process allows gradients to traverse the network with greater ease (Mark Sandler *et al.,* 2019).

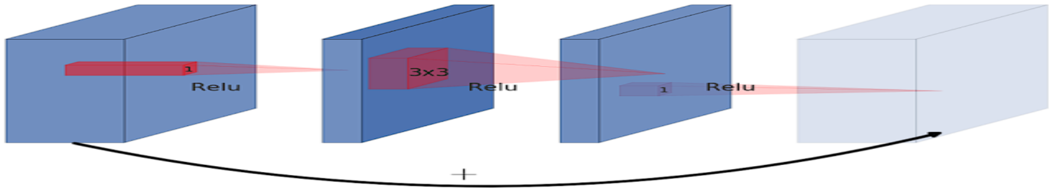

Figure3.
Residual block

An inverted residual block include 1 × 1 convolution to process the input feature map to the high dimensional space where depth wise convolution is carried out in this extended architecture. Finally, a following 1×1 convolution apply to restore feature map to the original feature dimension. The "inverted" part arises from the first expansion of the dimensionality at the beginning of the block and the second contraction at the end. This is different to the standard practice (Mark Sandler et al., 2019), which tends to expansional after the conclusion of the residual block.

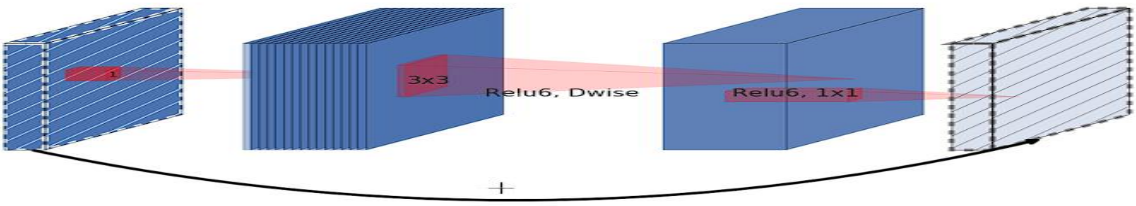

Figure 4.
Inverted residual block

Squeeze and Excitation

Squeeze-and-Excitation enables the model to focus on the crucial features and wait on the intimidating ones, (Jie Hu et al., 2019). There are two clearly separate phases of the execution:

- **Squeeze:** This phase combines the spatial dimensions (width and height) of the feature maps across each channel with one single value through global average pooling this creates a compact feature descriptor which synthesizes the whole distribution for each channel for each channel into one scalar value.
- **Excitation:** In this stage, the model produces a set of per-channel weights (activation weights or scores) by means of a fully connected layer that is applied after the squeeze step. The last step consists in using the learned importance scores to the original input feature map on perchannel basis and, hence, scaling all channels on their pertinent scores.

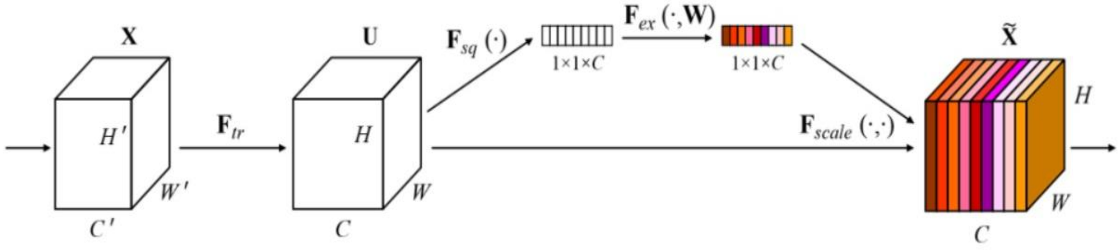

Figure 3.
Squeeze and Excitation block

This process allows the network to enhance more important features and down-weight less important ones, switching the feature maps according to the learned content of input images. In addition to that, EfficientNet is also designed to use the Swish activation function to improve accuracy and efficiency.

Here is the source for Fig 3.1,2,3,4,5,6,7,8,9 (https://viso.ai/deep-learning/efficientnet).

Swish Activation Function

Swish is a smooth, continuous function compared to the Rectified Linear Unit (ReLU) that is a piecewise linear function. Swish permits a small amount of negative weights to be passed, whereas the ReLU eliminates all negative weights by setting them to zero.

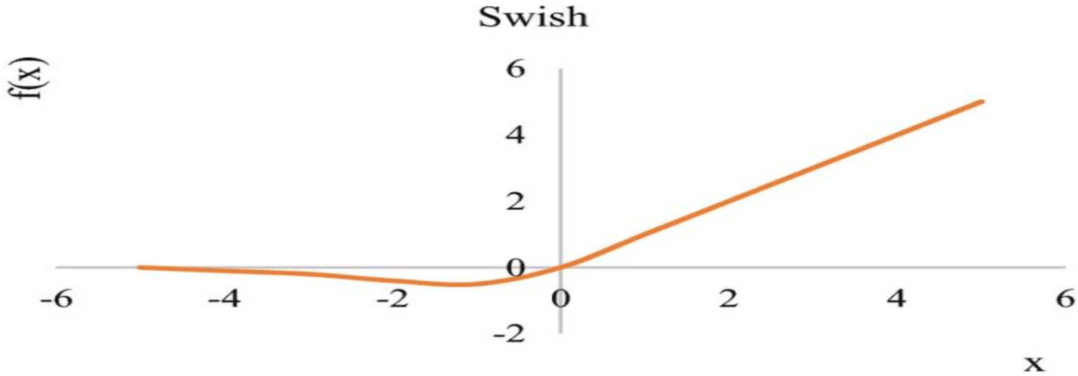

Figure 3.
Swish activation function

EfficientNet integrates all the aforementioned components into its architecture. Ultimately, the architecture is structured as follows:

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

Table 3.
Summary of EfficientNet network layering

WORKING OF THE PROPOSED MODEL

The number of fruit spots, fruit weight, fruit shape, fruit texture and fruit color are the essential features necessary for identifying a diseased fruit, which are extracted and utilized for training purposes. The architecture of the working model is illustrated in Figure 3.10. The flowchart of this study. The model extracted and resized the spatial features of the original images. Images were inputted, and through data analysis, the final output consists of the classification results.

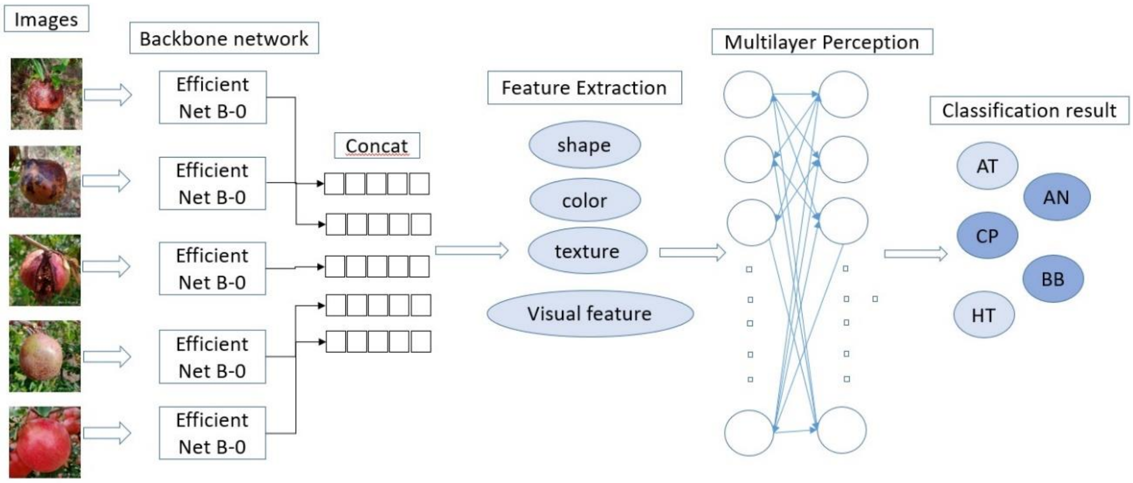

Figure 3.
The flow chart of this study

We can see the precise technical approach that was used for this research. First, we extracted the spatial features from the original images using EfficientNet-B0. EfficientNet, a convolutional neural network, served as the backbone architecture for extracting spatial features from pomegranate fruit images. The network was built around the mobile inverted bottleneck convolution (MBConv) module, which used the squeeze and excitation network idea within it. MBConv introduced stochastic depth to the model, thereby decreasing the training duration and enhancing performance. EfficientNet-B0 comprises 16 mobile inverted bottleneck convolution modules, 2 convolutional layers, 1 global average pooling layer, and 1 classification layer. The input image was resized to 224×224×3, and the operations were executed sequentially to achieve the results of the initial stage, second, feature fusion was done by combining the Efficient Net features with 1×1 convolution, a method that rearranges and combines features that are connected to make new features. The significance of new features is continually revised in accordance with the loss function to yield more optimal features. Finally, the integrated features were transmitted to the classification layer to execute the classification algorithm.

RESULTS AND DISCUSSION

After Pre-processing of the dataset the final dataset consists of 5,099 pomegranate fruit images. The dataset is partitioned into two subsets one for training and other for testing. The training dataset contain 4599 pomegranate fruit images and testing dataset contain 500 pomegranate fruit images. So the study's experimental results indicate that our proposed work attains an accuracy of 98.73%.

MODEL PERFOMANCE

The proposed model utilizes Efficient Net and is executed for 10 epochs to achieve convergence and attain optimal accuracy. Initially, this proposed model achieved a training accuracy of 81%. With each subsequent run, the model exhibited a marked increase in accuracy. After 10 iterations, accuracy has attained 98.73%. The augmentation of epochs clearly enhances the accuracy of classification.

```
Epoch 1/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 41s 2s/step - accuracy: 0.4247 - loss: 1.4312 - val_accuracy: 0.4600 - val_loss: 1.2485
Epoch 2/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 20s 2s/step - accuracy: 0.8184 - loss: 0.8353 - val_accuracy: 0.7500 - val_loss: 0.8423
Epoch 3/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 20s 1s/step - accuracy: 0.8978 - loss: 0.5517 - val_accuracy: 0.8400 - val_loss: 0.6326
Epoch 4/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 20s 2s/step - accuracy: 0.9274 - loss: 0.4117 - val_accuracy: 0.8300 - val_loss: 0.5398
Epoch 5/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 20s 2s/step - accuracy: 0.9521 - loss: 0.3343 - val_accuracy: 0.8700 - val_loss: 0.4621
Epoch 6/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 21s 2s/step - accuracy: 0.9660 - loss: 0.2691 - val_accuracy: 0.8900 - val_loss: 0.4067
Epoch 7/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 21s 2s/step - accuracy: 0.9853 - loss: 0.2302 - val_accuracy: 0.9000 - val_loss: 0.3605
Epoch 8/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 18s 1s/step - accuracy: 0.9860 - loss: 0.2075 - val_accuracy: 0.9100 - val_loss: 0.3337
Epoch 9/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 21s 2s/step - accuracy: 0.9858 - loss: 0.1885 - val_accuracy: 0.9100 - val_loss: 0.3075
Epoch 10/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 20s 2s/step - accuracy: 0.9873 - loss: 0.1652 - val_accuracy: 0.9200 - val_loss: 0.2881
```

Figure 4.
Model Performance

Confusion Metrics

The confusion matrix offers an in-depth analysis of the models predictions, by specifying counts for true positives, true negatives, false positives, and false negatives. This helps in comprehending the models performance with greater detail. Figure 4.2 presents the confusion matrix of the model. Figures 4.3 illustrate the accuracy and loss curves for both training and testing data, respectively. The model demonstrates substantial efficacy in testing and classifying pomegranate fruits, achieving an accuracy of 98.73%.

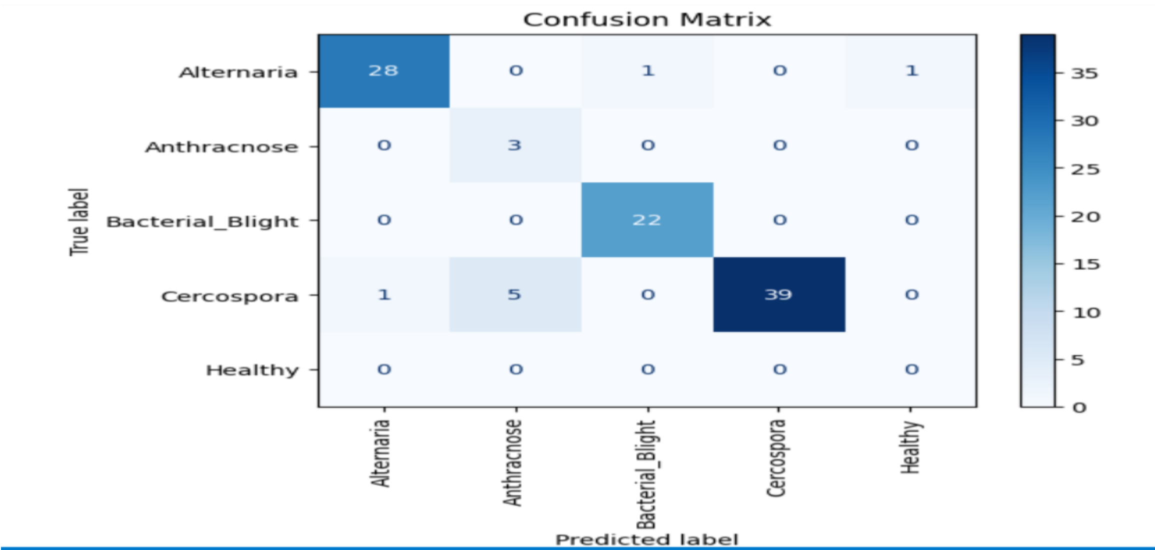

Figure5.
Disease based confusion matrix of Efficient Net
The TP, FP, TN, and FN of each disease using Efficient Net are given in Table 4.1.

Table 4.
Manipulation of Confusion matrix of Efficient Net

Disease Name	TP	TN	FP	FN
Alternaria	28	69	1	2
Anthraconose	3	92	5	0
Bacterial Blight	22	77	1	0
Cercospora	39	55	0	6
Healthy	0	99	1	0

The accuracy of validation and training data of Efficient Net is shown in Fig. 4.3.

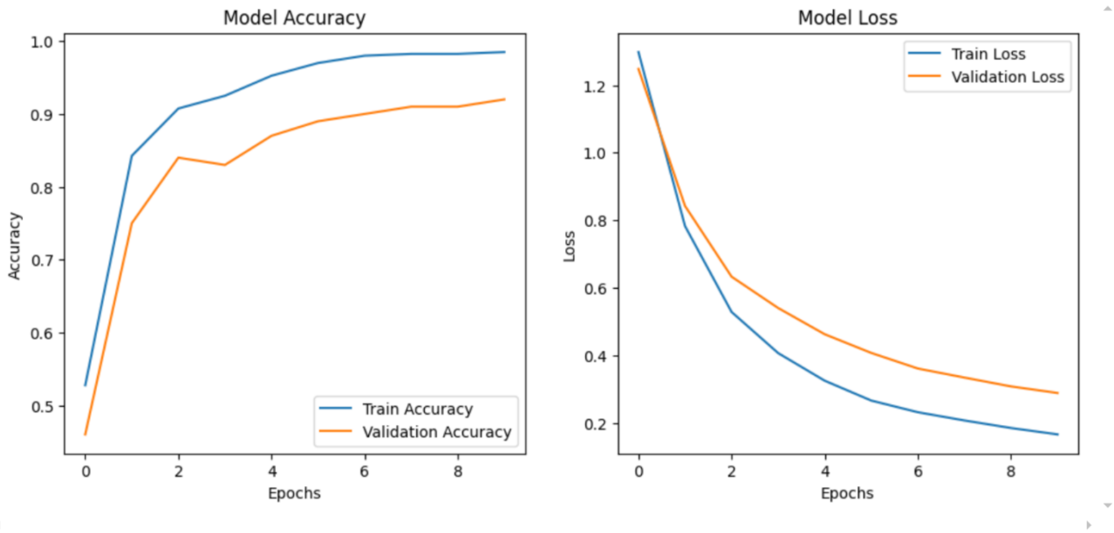

Figure 6
Accuracy model curve Efficient Net model
The model achieved an accuracy of 98.73% based on the parameters outlined in Table 4.2.In addition to accuracy, other metrics such as , Precision, and specificity have been assessed to evaluate overall performance.

Table 4.
Model Performance on Test Data

Metrics	Alternaria	Anthracnose	Bacterial Blight	Cercospora	Healthy	Overall
Accuracy	0.9700	0.9500	0.9900	0.9400	0.9900	**0.9873**
Sensitivity	0.9300	1.0000	1.000	0.8600	1.0000	**0.9800**
Specificity	0.9800	0.9400	1.000	0.9800	1.0000	**0.9984**

ROC CURVE

The ROC curve illustrates the true positive rate (sensitivity) against the false positive rate (1-specificity). The Area under the curve (AUC) is a single scalar value that summarizes the performance of the model.

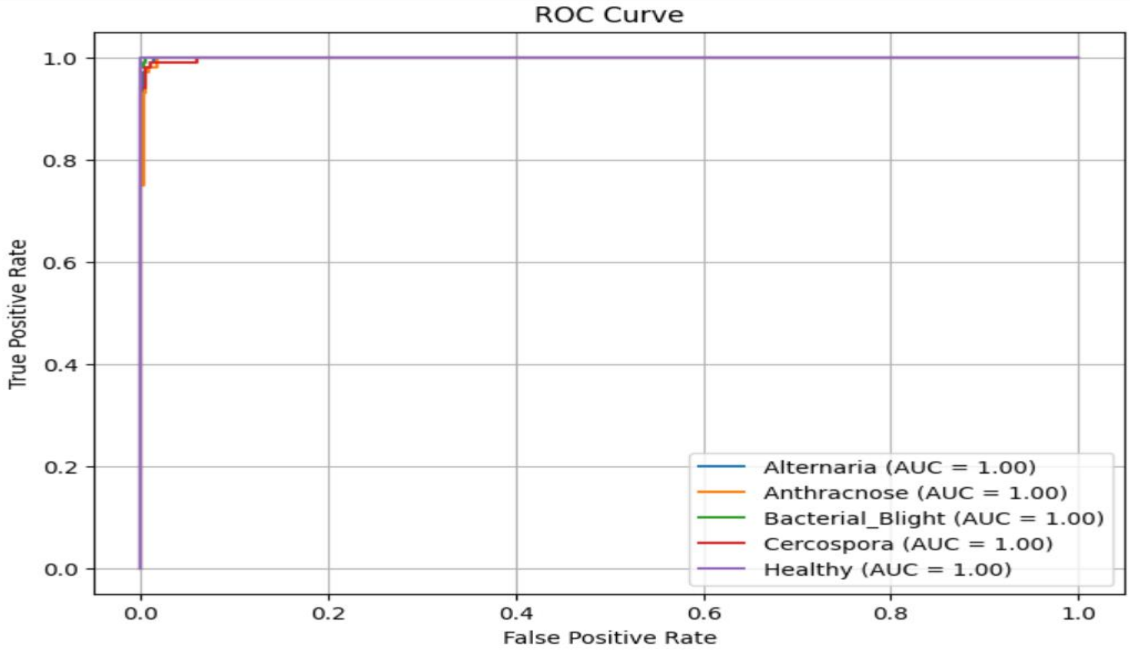

Figure 7
ROC Curve

This study utilizes the EfficientNet model to classify pomegranate fruits and suggests strategies aimed at enhancing export quality and refining marketing practices. This reduces the time needed for manual disease detection and helps clarify uncertainties for local farmers.

CONCLUSION

Pomegranates have been a popular fruit for their health benefits from a long time, and are even more helpful for the immune system because of their antimicrobial properties. Several types of fruit and leaf diseases affect pomegranate production in large scale as they affect in quantity and quality of the product. In smart farming, the automatic detection of plant disease is critical task which has attracted much attention from researchers in recent time. Advances in deep learning can be of assistance with the presence of crop disease diagnosis as well as prediction. ML and DL models can identify and classify fruit diseases which result in increase of crop productivity. A model based on the EfficientNet has been devised to classify disease affected fruits. The model was train and tested using Pomegranates fruits diseases dataset for deep learning model. The study's experimental results indicate that our proposed work attains an accuracy of 98.73%. This shows the model's efficiency and capability of discriminating several disease types, including Healthy, Bacterial Blight, Anthracanose, Alternaria, and Cercospera. For future applications the proposed models will use non-invasive real-time recognition to obtain fruit images through remote sensing. This would be a great help for farmers in an early detection of disease. In addition, the developed models could be easily adapted for detection of a variety of other fruit and plant diseases, beyond those affecting pomegranate fruits. Also the models proposed in this thesis can be now expanded to enable predict in real-time the quality of vegetable and fruits, by use of IoT devices. Moreover, the proposed model could be progressed into an android app where smartphone would enable growers to take images of their plants or fruits in real time to receive instant classification reports related to plant or fruits diseases.

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Authors' contributions: Each author participated equally in the creation of this work.

Conflicts of Interest: The authors declare no conflict of interest.

Consent to Participate: Yes

Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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