A Dissertation on

# A Novel Approach for Fruit Classification using Learnable Weighted Skip Connections in Depthwise Separable Convolution

Submitted to

Department of Computer Science
School of Computer Sciences

By


**Sumant Kumar**
22PGMCA36
MCA IV Semester


Under the Guidance of


**Dr. Gururaj Mukarambi**
Senior Assistant Professor
Department of Computer Science



Central University of Karnataka
Kadaganchi, Kalaburagi - 585367, INDIA
*July, 2024*

A Dissertation on

# A Novel Approach for Fruit Classification using Learnable Weighted Skip Connections in Depthwise Separable Convolution

Submitted to

Department of Computer Science
School of Computer Sciences

By


**Sumant Kumar**

22PGMCA36

MCA IV Semester


Under the Guidance of


**Dr. Gururaj Mukarambi**

Senior Assistant Professor

Department of Computer Science



Central University of Karnataka
Kadaganchi, Kalaburagi - 585367, INDIA

*July, 2024*

ಕರ್ನಾಟಕ ಕೇಂದ್ರೀಯ ವಿಶ್ವವಿದ್ಯಾಲಯ
कर्नाटक केंद्रीय विश्वविद्यालय
CENTRAL UNIVERSITY OF KARNATAKA
(Established by an Act of the Parliament in 2009)
Kadaganchi, Kalaburagi – 585367, INDIA, Website: www.cuk.ac.in
Block No.17, CUK Campus

Dept. of Computer Science

*Email: hodcs@cuk.ac.in*

School of Computer Sciences

# CERTIFICATE

This is to certify that the dissertation entitled as **"A Novel Approach for Fruit Classification using Learnable Weighted Skip Connections in Depthwise Separable Convolution"** submitted by **Sumant Kumar** bearing Registration Number: **22PGMCA36**, studying in MCA IV Semester, to the Department of Computer Science, Central University of Karnataka, Kadaganchi, Kalaburagi, is a record of the original work carried out by him under my guidance and supervision during the IV semester of MCA program. The work embodied in this dissertation has not been submitted fully or in part any where else.

Guide
**Dr. Gururaj Mukarambi**
Senior Assistant Professor
Dept. of Computer Science

Head
Dept. of Computer Science
School of Computer Science

**Name and Signature of Examiner**

1. ..........................................................................................................

2. ..........................................................................................................

# DECLARATION

I hereby declare that the work embodied in this dissertation, which is entitled as **"A Novel Approach for Fruit Classification using Learnable Weighted Skip Connections in Depthwise Separable Convolution"**, submitted to Department of Computer Science, Central University of Karnataka, Kadaganchi, Kalaburagi is a record of my original work carried out by me in the Department of Computer Science, Central University of Karnataka, under the guidance of **Dr. Gururaj Mukarambi**, and that the full of part of this dissertation has not been submitted to this or any other University or Institute.

Place: Kadaganchi
Date: July 08, 2024

**Sumant Kumar**
MCA IV Semester
Central University of Karnataka
Kadaganchi, Kalaburagi

# Acknowledgements

I would like to express my sincere gratitude to the Central University of Karnataka, for their support and guidance in the completion of this dissertation. I am particularly grateful to the Honorable Vice-Chancellor, Prof. Battu Satyanarayana, for his vision and leadership.

I would also like to thank the Dean and the Head of the School of Computer Science, Prof. Srikantaiah K C for their encouragement and support.

I would like to extend heartfelt appreciation to my guide **Dr. Gururaj Mukarambi** for his valuable insights, suggestions and guidance. Their expertise and insights have greatly contributed to the successful completion of this work.

I am deeply grateful to the learned faculties of the Department of Computer Science, Prof. R S Hegadi, Dr. Nagaraj Dharwadkar, Dr. P M Kamble, Dr. Kagale Madhuri, Dr. Sukanya S. Gaikwad, Mrs. Poornima E. G. for their valuable guidance, support, and encouragement throughout the course of this dissertation.

Furthermore, I would like to acknowledge my classmates for their camaraderie and motivation, and intellectual discussions, which enriched my learning experience and provided a supportive environment for academic growth.

Last but not least, I would like to express my deepest gratitude to my family for their unwavering love, understanding, and encouragement throughout my academic journey. Their constant support has been the driving force behind my achievements.

Place: Kadaganchi
Date: July 08, 2024

**Sumant Kumar**
MCA IV Semester
Central University of Karnataka
Kadaganchi, Kalaburagi

# Abstract

Automation in agriculture is vital for enhancing productivity and sustainability. In our research, we propose a novel approach for fruit classification using Depthwise Separable Convolutional Networks with Learnable Weighted Skip Connections. To minimize the number of parameters and computational cost, we employ depthwise separable convolutions instead of standard convolutions. This technique involves applying convolution operations channel-wise followed by pointwise convolutions, significantly reducing the model's complexity. To mitigate overfitting and effectively summarize the feature maps, we integrate a Global Average Pooling layer. We validate our model's performance using the Fruit-360 dataset. The first version of this dataset contains 55,244 images across 81 categories, split into 41,322 training images and 13,877 test images. The second version comprises 90,483 images of 131 fruit categories, divided into 67,692 training images and 22,688 test images. Our experimental results demonstrate that the proposed model achieves a classification accuracy of 99.25% on the first version and 99.29% on the second version of the Fruit-360 dataset. Furthermore, we compare the performance of our proposed model with other state-of-the-art CNN models. Our findings indicate that our model outperforms other models existing in the literature in terms of fruit classification accuracy. This advancement in automated fruit classification has significant implications for agricultural efficiency and productivity, offering a robust solution to meet the increasing demands of the agricultural sector.

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Introduction

Agriculture is an essential sector that sustains a significant portion of the global population. With the increasing demand for food production and the necessity for efficient agricultural practices, automation in this field has become crucial. The automation of fruit classification, in particular, holds immense potential for improving productivity and ensuring quality control. Traditional methods of fruit classification are labor-intensive and prone to human error, making automated systems an attractive alternative.

Convolutional neural networks (CNNs) have demonstrated impressive performance in a range of image classification tasks in recent years. However, a lot of parameters are frequently included in common CNN architectures, which raises the possibility of overfitting and results in significant computational costs. We provide a novel method for fruit categorization using Depthwise Separable Convolutional Networks with Learnable Weighted Skip Connections in order to overcome these difficulties. Using depthwise separable convolutions, which operate channel-wise and then execute pointwise convolutions, this method drastically lowers the number of parameters and computing expense.

Five Depthwise Separable Convolutional layers and two Pointwise Convolutional layers make up our model architecture, with two of the depthwise separable layers including strides. We incorporate a Global Average Pooling layer to enable robust feature extraction and prevent overfitting. This solution keeps the model's excellent accuracy in classification tasks while also improving its efficiency.

We assess the effectiveness of our suggested model on the Fruit-360 dataset, an extensive dataset that is frequently utilized in studies on fruit categorization. This dataset has two versions: the first has 55,244 images in 81 categories, while the second has 90,483 images in 131 categories. Our test findings show that the suggested model achieves exceptional classification accuracy, with 99.25% on the first and 99.29% on the second Fruit-360 dataset versions.

In comparison to other cutting-edge CNN models, our suggested model has performed better, proving the efficacy of our methodology. This research highlights the potential of cutting-edge neural network designs in real-world agricultural applications in addition to making contributions to the field of automated fruit classification. Our goal is to improve fruit classification's accuracy and efficiency so that the agriculture industry can fulfill the growing needs for food production and quality assurance.

## 1.1 Background

Fruit categorization is an important agricultural task that supports grading, sorting, and quality control, among other activities. Conventional techniques for classifying fruits are frequently labor-intensive, manual, and prone to human mistake. These techniques, particularly in large-scale operations, can be unreliable and inefficient. This procedure could be completely changed by automated fruit categorization that makes use of deep learning and computer vision to provide fast, reliable, and accurate classification.

CNNs, or convolutional neural networks, have become a potent tool for tasks involving picture recognition and classification. CNNs are excellent for difficult tasks like fruit classification because they can automatically learn and extract pertinent information from photos. Nevertheless, a number of obstacles confront the current CNN-based methods for classifying fruits, such as high processing requirements, sizable model sizes, and difficulty with accessibility and implementation.

The Fruit-360 dataset, a comprehensive collection of fruit images, has become a standard benchmark for evaluating fruit classification models. This dataset includes two versions: the first version consists of 55,244 images of 81 fruit categories, while the second version contains 90,483 images of 131 fruit categories. Despite the availability of such datasets, achieving high accuracy in fruit classification remains challenging due to factors such as variations in lighting, occlusions, and the natural variability of fruit appearances.

This project intends to create a novel fruit categorization system that makes use of cutting-edge deep learning techniques in order to overcome these issues. Our goal is to develop a system that is not only efficient but also scalable and user-friendly by concentrating on lowering the computational complexity of the model and enhancing its accuracy. The model's usefulness is further improved by its deployment on the Hugging Face platform and its integration into an Android app, which makes it a workable solution for actual agricultural applications.

## 1.2 Motivation

The motivation behind this project stems from the urgent need to solve important issues facing the agriculture industry, namely with regard to fruit identification and classification. Global economies are based mostly on agriculture, which is essential for maintaining livelihoods, guaranteeing food security, and promoting economic growth. Fruit classification using traditional methods frequently relies on manual examination, which is time-consuming, labor-intensive, and prone to human mistake. Furthermore, the requirement for automated and intelligent solutions grows as agricultural operations expand to meet rising demand.

This initiative is primarily driven by its potential to promote sustainability, efficiency, and innovation in the agriculture industry. Our goal is to help agriculture become a more resilient and technologically advanced sector that can tackle the problems of the twenty-first century. To this end, we are working toward the development of robust and reliable fruit recognition and classification systems.

## 1.3 Existing System

More sophisticated fruit classification systems have been created with the introduction of deep learning, especially CNNs. With CNN-based models, classification accuracy can be greatly increased by automatically learning and extracting hierarchical features from images. Among the noteworthy current systems are:

- **Basic CNN Models:** These models consist of multiple convolutional and pooling layers followed by fully connected layers. While they provide good accuracy, they often require large amounts of computational resources and memory, making them less practical for deployment on resource-constrained devices.

- **Transfer Learning:** This approach involves using pre-trained CNN models, such as VGG, ResNets, or Inception, which have been trained on large datasets like ImageNet. These models are then fine-tuned on fruit datasets to improve classification accuracy. Although transfer learning can enhance performance, it still faces challenges related to model size and computational demands.

- **Data Augmentation and Regularization:** Techniques such as data augmentation (e.g., rotations, translations, and flips) and regularization methods (e.g., dropout and batch normalization) have been employed to improve the robustness and generalization of CNN models. These techniques help mitigate overfitting but do not address the inherent complexity and size of the models.

- **Ensemble Methods:** Combining multiple CNN models to form an ensemble can boost classification accuracy. However, this approach increases the computational and memory requirements, making it less feasible for real-time applications and deployment on mobile devices.

Despite the advancements in deep learning for fruit classification, existing systems still face several limitations:

- **High Computational Complexity:** Many CNN models require significant computational power and memory, limiting their applicability in resource-constrained environments.

- **Large Model Sizes** The size of the models can be prohibitive for deployment on mobile devices or embedded systems, where storage and memory are limited.

- **Scalability Issues:** Existing systems may struggle to scale effectively with larger datasets or more fruit categories, impacting their generalizability and performance.

- **Accessibility:** Deploying and accessing these models can be challenging for end-users, particularly those in agricultural sectors who may lack technical expertise.

## 1.4 Proposed System

Our proposed system utilizes Depthwise Separable Convolution with the Learnable Weighted Skip Connections to enhance classification accuracy and efficiency. The model is designed to be both powerful and computationally efficient, making it suitable for deployment on various platforms, including mobile devices.

- **Depthwise Convolution:** Compared to normal convolutions, this step drastically decreases the number of parameters by convolving each input channel with a single filter.

- **Pointwise Convolution:** The output from the depthwise step is combined using a 1x1 pointwise convolution subsequent to the depthwise convolution. By reducing computational complexity and parameter count in two steps, this method improves model efficiency without sacrificing accuracy.

- **Skip Connections:** Remaining connections, as they are also called, aid in reducing the vanishing gradient issue by improving the gradient's ability to propagate through the network during backpropagation.

- **Learnable Weighted Skip Connections:** In our model, skip connections are adaptive in nature, by learning how much weight it should give to the skip connections during training of the model. This prioritizes more important features and improves the overall learning process.

- **Global Averege Pooling Layer:** GAP layer replaces traditional fully connected layers by averaging the spatial dimensions of the feature maps, which reduces the total number of parameters and helps prevent overfitting. GAP layers also aggregate information across entire feature maps, ensuring robust feature representation.

The proposed system offers a comprehensive solution for automated fruit classification, addressing the limitations of existing methods by improving efficiency, accuracy, and accessibility.

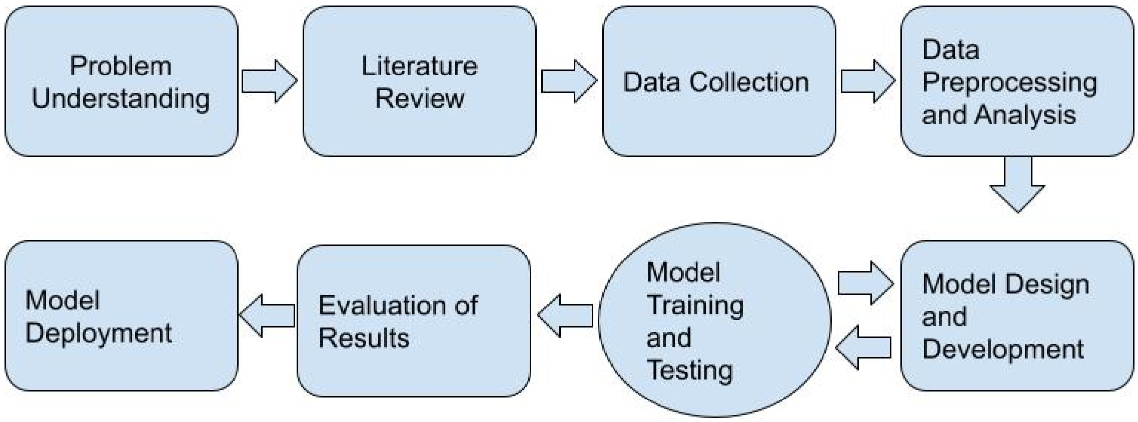


Figure 1.1: The workflow of the proposed system

# Chapter 2

# Literature Survey

Kausar and Sharif introduce a novel deep learning framework, Pure-CNN, designed specifically for the classification of fruit images. This framework leverages the convolutional neural network architecture to effectively classify a wide variety of fruits by their visual features. The study utilizes the Fruit-360 dataset, comprising 81 categories and a total of 55,244 images. Pure-CNN is designed with multiple convolutional layers, ReLU activations, and a global average pooling layer to enhance feature extraction and classification accuracy. The research demonstrates that Pure-CNN achieves a high classification accuracy of 98.88%, outperforming several other models in terms of computational efficiency and accuracy.[1]

Dr. Rathnayake present an innovative approach to fruit classification using the Cascaded Adaptive Neuro-Fuzzy Inference System (Cascaded-ANFIS). The key contributions include the use of nine state-of-the-art feature descriptors such as Color

Structure (CS), Region Shape (RS), and Scale-Invariant Feature Transform (SIFT). The research focuses on the classification of a dataset containing 131 fruit classes and employs feature reduction methods to manage dimensionality. The proposed algorithm demonstrates a high classification accuracy of 98.36%, outperforming several existing models such as CNN with various optimization techniques and customized versions of MobileNet and Inception V3.[2]

Ziliang Huang explores the application of transfer learning to improve fruit recognition tasks. The research leverages a pre-trained CNN model and adapts it for classifying a new set of fruit categories by retraining the classifier on top of the pre-trained network. This approach allows the model to repurpose previously learned features, significantly improving classification accuracy on the new dataset. The study highlights the effectiveness of transfer learning in scenarios where limited training samples are available, achieving superior performance compared to traditional training methods.[3]

Miaorun Lin proposes a robust method for fruit classification using the ResNet model integrated with an attention mechanism. This study addresses the inefficiencies of traditional manual classification methods by leveraging transfer learning techniques and automated feature detection. By incorporating the attention module into ResNet, the model can effectively focus on significant image features, improving classification accuracy. The research concludes that this approach not only enhances recognition accuracy but also demonstrates the practical viability of using advanced deep learning models in agricultural applications, offering a significant improvement over existing methods.[4]

Ukwuoma and Zhiguang provide a comprehensive overview of recent advancements in fruit detection and classification using deep learning techniques. Their study emphasizes the need for efficient automated fruit classification methods to overcome the limitations of traditional manual approaches. They evaluate various deep learning models and architectures, focusing on their application in fruit detection and classification tasks. The paper highlights the effectiveness of models like ResNet-50 in achieving high accuracy and robustness in classification, and discusses challenges such as dataset variability and computational efficiency. The research concludes with insights into the future potential of deep learning in enhancing agricultural productivity and automation.[5]

Dr. Zhu proposes a novel approach to fruit classification using convolutional neural networks (CNNs) and data augmentation techniques. The study highlights the limitations of traditional feature-based machine learning methods and introduces the IANet, an optimized 10-layer network derived from AlexNet. Utilizing data augmentation on the Fruits-360 dataset, the IANet significantly enhances classification performance. The paper demonstrates that IANet achieves 98.60% accuracy with data augmentation, outperforming other models such as AlexNet, 13-Layer CNN, and HoreaCNN, thus presenting a robust solution for automated fruit classification.[6]

Mohit Dandekar propose an innovative approach to fruit classification, addressing the challenge posed by deceptively similar classes. The study highlights the limitations of traditional deep learning models that rely solely on the transformed features from the rearmost layers for classification. Instead, Dandekar leverage an ensemble method utilizing activations from multiple CNN layers to better handle multi-granular data. This method enhances the classification of objects with similar appearances by using these multi-layer activations to build multiple deep decision trees (Random Forest). The Fruits-360 dataset was used for evaluation, and the proposed model demonstrated superior performance compared to conventional deep learning approaches, showcasing its potential in industrial applications for autonomous detection and classification of objects with high multi-granular similarities.[7]

Mureșan and Oltean introduced a high-quality dataset of fruit images and conducted experiments using neural networks for fruit detection and classification. The paper discusses the rationale behind selecting fruits for this study and proposes several practical applications for such classifiers. The dataset and the experimental results contribute to the ongoing research in automated fruit classification, showcasing the potential of deep learning models in this domain.[8]

# Chapter 3

# Problem Definition and Objectives

Deep learning-based automated fruit classification has become a viable way to improve agricultural output and operations. Nonetheless, there are frequently major issues with accuracy, scalability, and user accessibility with current methods. These difficulties may prevent automated systems from being widely adopted and used in actual agricultural situations. Fruit categorization requires a high degree of accuracy in order for the system to consistently distinguish between various fruit groups. Many existing techniques fail to reach the necessary high precision levels. Another crucial factor is scalability, since models need to be able to manage big datasets and change to accommodate various fruit varieties without incurring appreciable additional computing costs. Another issue is user accessibility, which makes it challenging for non-experts to use efficiently. By creating an effective and user-friendly fruit categorization system based on learnable weighted skip connections in depthwise separable convolution, this project seeks to overcome these issues.

The following are the project's primary goals:

- **Developing Efficient Model:** We have developed a depthwise separable convolutional model which leverages the power of learnable weighted skip connections. This model utilizes depthwise separable convolutions to minimize the number of parameters and reduce computational complexity, making it both accurate and efficient. The model consists of five Depthwise Separable Convolutional layers, two pointwise convolution layers, three learnable weighted skip connections, and a Global Average Pooling (GAP) layer to prevent overfitting and aggregate information across feature maps.

- **Deployment on Hugging Face:** The trained model has been deployed on the Hugging Face platform, which provides an accessible and scalable environment for hosting machine-learning models. This deployment ensures that the model can be easily accessed and utilized by users worldwide, leveraging Hugging Face's infrastructure for high availability and performance.

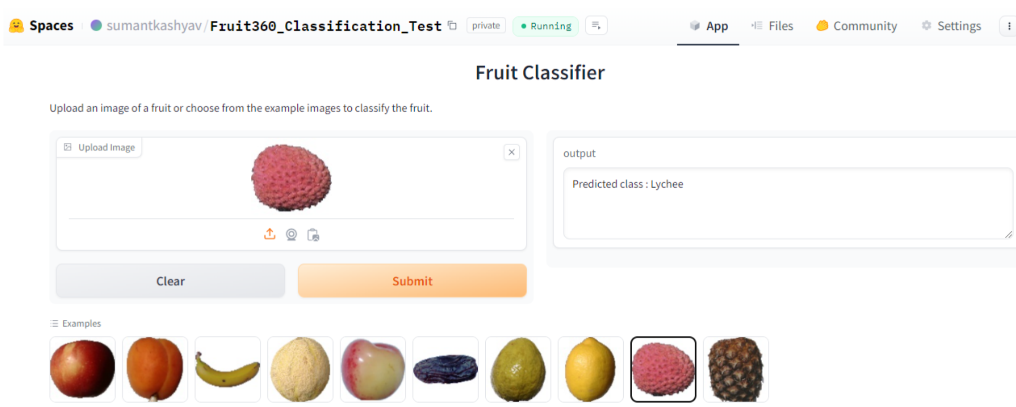


Figure 3.1: Huggingface space user interface

- **Integration with Android App:** To enhance user accessibility, the fruit classification model has been integrated into a dedicated Android app. This app allows users to classify fruit images in real time using their mobile devices.

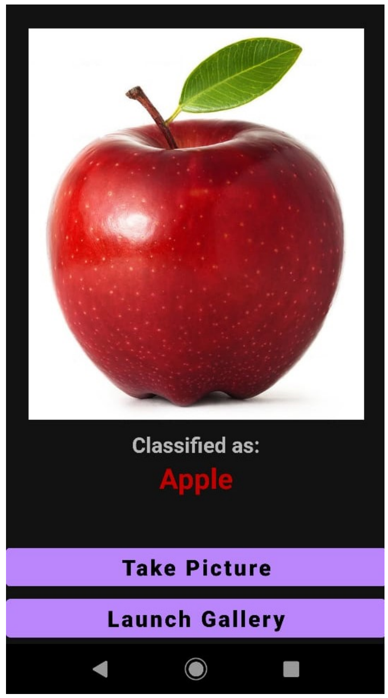


Figure 3.2: Android application user interface

- **Classification on Real-time:** Users can use the camera on their cellphone to take pictures of fruit and get classification results right away.

- **User-friendly Interface:** The app is designed with an intuitive interface, making it easy to use for farmers, agricultural professionals, and consumers.

- **Offline Functionality:** By leveraging on-device processing, the app can function offline, ensuring usability even in areas with limited internet connectivity.

# Chapter 4

# Implementation

## 4.1 Hardware Specifications

- Processor: i5 or above.
- Memory: Minimum 16 GB.
- GPU: Minimum 16 GB.

## 4.2 Software Specifications

- Operating System: Windows 10 and above.
- Languages: Python, Tensorflow-keras Framework.
- IDE: Kaggle Notebook, Google Colab.

## 4.3 Methodology

Methodologies used during project the development process are sets of rules and processes that define how you manage a project. They help you plan, execute, monitor, and control the project activities and deliverables. Various approaches offer varying benefits and drawbacks, contingent on the type, extent, and objectives of the undertaking. This project was developed using a number of technologies and processes. The following outlines the methodology employed in the project:

- **Technology Selection**

  Python was chosen as the primary technology for building the project. The tensorflow framework has been used for model building, training, and testing. Many libraries such as numpy, pandas, sci-kit learn, and matplotlib etc. were used for the accomplishment of the project.

- **Data Collection**

  The fruit-360 dataset has been used in this project, available on Kaggle. The Fruit-360 dataset, a comprehensive collection of fruit images, has become a standard benchmark for evaluating fruit classification models. This dataset includes two versions: the first version of this dataset consists of 55,244 images with 81 categories, divided into 41,322 training images and 13,877 test images. The second version contains 90,483 images of 131 fruit categories, divided into 67,692 training images and 22,688 test images. Every image had a white backdrop and measured 100 x 100 pixels in size.


Figure 4.1: Fruit-360: A single image taken from every category

- **Model Selection and Architecture Design**

  In developing an automated fruit classification system, selecting an appropriate model and designing an efficient architecture are critical steps. Our proposed model, the Depthwise Separable Convolution with Learnable Weighted Skip Connections, addresses the challenges of computational complexity, model size, and classification accuracy, making it an ideal choice.

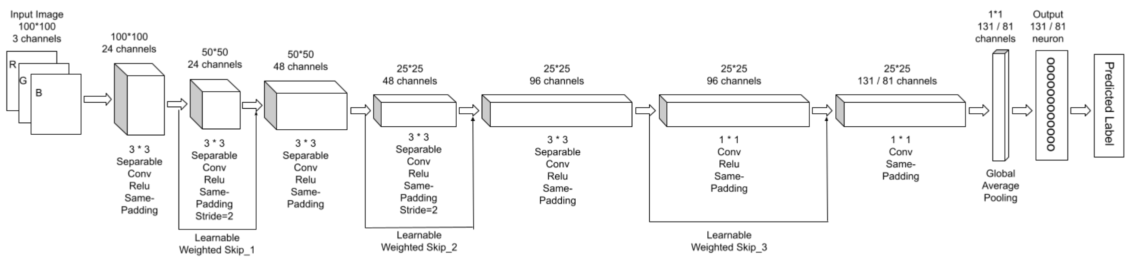


Figure 4.2: Proposed model architecture

  The model consists of five depthwise separable convolutional layers and two pointwise convolution layers. Two of the depthwise separable layers: second and fourth, followed by stride operations. We employed a global average pooling layer to average all of the feature maps and lessen overfitting. The learnable weighted skip connections are used at three places.

  The architecture of our proposed model "Depthwise Separable Convolution with Learnable Weighted Skip Connections" is designed to balance efficiency and performance. Below are the key components and their functions:

  - **Input Layer:** Accepts the input image, it is resized to a fixed dimension of 100x100 pixels suitable for processing the fruit images.

– **Depthwise Separable Convolutional Layers:** To minimize the number of parameters and computational cost dramatically, we employed depthwise separable convolutions. In order to reduce computations and create a lighter model, this method splits a normal convolution into two parts: a depthwise convolution and a pointwise convolution. This efficiency is essential for using the model on low-resource devices, such as smartphones.

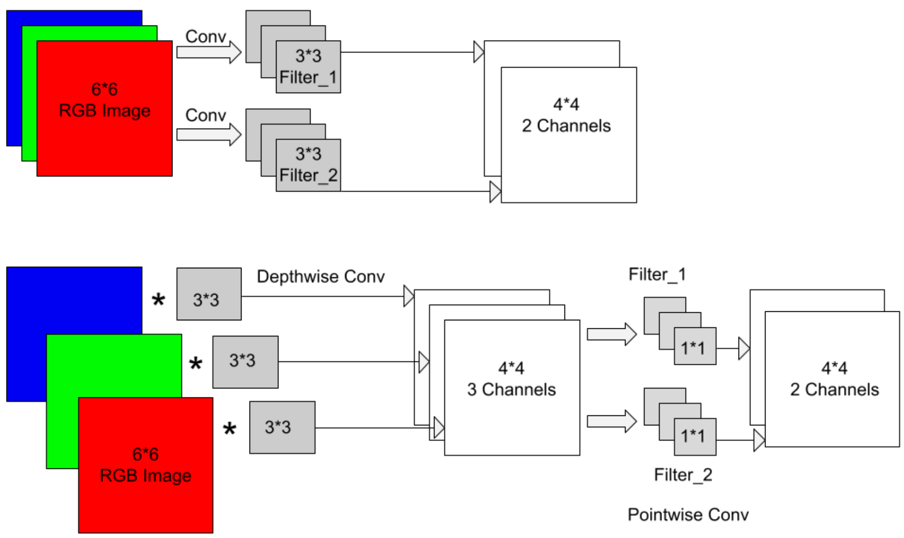


Figure 4.3: Normal convolution vs depthwise separable convolution.

**Parameters of Normal Convolution:** For above example.

$$(3 \times 3 \times 3 + 1) \times 2 = 56$$

**Parameters of Depthwise Separable Convolution:**

$$(3 \times 3 + 1) \times 3 + (1 \times 1 \times 1 + 1) \times 2 = 34$$

**Computation cost of Normal Convolution:** For above example.

$$(3 \times 3 \times 3) \times (4 \times 4 \times 2) = 864$$

**Computation cost of Depthwise Separable Convolution:**

$$(3 \times 3) \times (4 \times 4 \times 3) + (1 \times 1 \times 3) \times (4 \times 4 \times 2) = 528$$

– **Stride Layers:** Two of the depthwise separable convolutional layers are followed by stride layers, which downsample the feature maps by half, to reduce their spatial dimensions and the computational load.

– **Learnable Weighted Skip Connections:** Skip connections are incorporated to help mitigate the vanishing gradient problem and allow gradients to flow more effectively through the network during backpropagation. We utilized a custom layer named "WeightedSkipConnection" to create learnable weights, which learn to weight the skip connections during model training. The skip connections are initially weighted from 0 to 1 using the RandomUniform function available in TensorFlow. During the model's training, these weights learn to adjust the skip connections to minimize the loss function through backpropagation. These adaptive skip connections enable the model to prioritize the most relevant features, enhancing its ability to learn and emphasize critical information.

**Learnable Weighted Skip Convolution Equation:**

$$\text{new\_feature\_map} = \text{current\_feature\_map} + \text{skip\_feature\_map} \times \text{learnable\_weight} \quad (4.1)$$

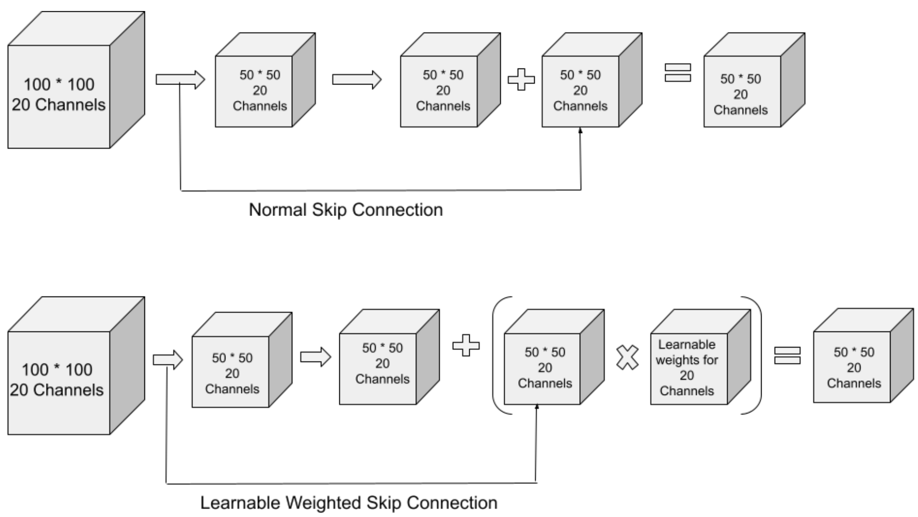


Figure 4.4: Normal skip vs learnable weighted skip connections

Three locations in which the Learnable Weighted Skip Connections are used are as follows: the first skip connection adds input from the first depthwise separable convolution layer to the output of the second depthwise separable convolution layer before the activation function; the second skip connection adds input from the third depthwise separable convolution layer to the output of the fourth depthwise separable convolution layer before the activation function; and the third skip connection adds input from the fifth depthwise separable convolution layer to the output of the sixth pointwise convolution layer before the activation function.

- **Global Average Pooling (GAP) Layer:** In order to mitigate overfitting and compile data from full feature maps, a Global Average Pooling (GAP) layer was employed. By averaging the spatial dimensions of the feature maps, lowering the number of parameters, and improving the resilience of the feature representation, GAP substitutes the conventional fully linked layers.
- **Output Layer:** The final classification output is a fully connected layer that is followed by a softmax activation function; this corresponds to the anticipated fruit category.
- **Activation function:** For the multilabel classification of the fruit classes, we employed a softmax activation function at the outer layer of the model and the ReLU activation function at the inner layers of the model.

The following is the definition of the ReLU (Rectified Linear Unit) activation function:

$$\mathrm{ReLU}(x) = \max(0, x) \tag{4.2}$$

The definition of the Softmax activation function is:

$$\mathrm{Softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}} \tag{4.3}$$

| Layer (type) | Output Shape | Parameters | Connected to (Previous) |
| --- | --- | --- | --- |
| InputLayer | (None,100,100,3) | 0 | --- |
| SeparableConv2D | (None, 100, 100,24) | 123 | input_layer |
| ReLU | (None,100,100,24) | 0 | separable_conv2d |
| SeparableConv2D | (None, 50, 50,24) | 816 | relu |
| MaxPooling2D | (None, 50, 50,24) | 0 | relu |
| WeightedSkipConnection | (None,50,50,24) | 24 | separable_conv2d<br>max_pooling2d |
| ReLU | (None,50,50,24) | 0 | weighted_skip_connection |
| SeparableConv2D | (None,50,50,48) | 1,416 | relu |
| ReLU | (None,50,50,48) | 0 | separable_conv2d |
| SeparableConv2D | (None,25,25,48) | 2,784 | relu |
| MaxPooling2D | (None,25,25,48) | 0 | relu |
| WeightedSkipConnection | (None,25,25,48) | 48 | separable_conv2d<br>max_pooling2d |
| ReLU | (None,25,25,48) | 0 | weighted_skip_connection |
| SeparableConv2D | (None,25,25,96) | 5,136 | relu |
| ReLU | (None,25,25,96) | 0 | separable_conv2d |
| Conv2D | (None,25,25,96) | 9,312 | relu |
| WeightedSkipConnection | (None,25,25,96) | 96 | conv2d, relu |
| ReLU | (None,25,25,96) | 0 | weighted_skip_connection |
| Conv2D | (None,25,25,81 or 131) | 7,857 or 12,707 | relu |
| GlobalAveragePooling | (None, 81 or 131) | 0 | conv2d |
| Dense | (None, 81 or 131) | 6,642 or 17,292 | global_average_pooling |

Figure 4.5: Proposed model summary

# Chapter 5

# Results and Discussion

## 5.1 Experimental Analysis

All the tasks were implemented on the Kaggle notebook. The technology used was Python and Tensorflow-keras framework. Python being the core programming language and TensorFlow being framework for building the deep learning models. We used Fruit-360 dataset, which having two versions. First version of this dataset consists of 55,244 images with 81 categories, divided into 41,322 training images and 13,877 test images. We divided the test images into validation and test images, the validation contains 9713 images and the test contains 4164 images. The second version of Fruit-360 dataset contains 90,483 images of 131 fruit categories, divided into 67,692 training images and 22,688 test images. Here aslo we divided the test images into validation and test images, the validation contains 15881 images and the test contains 6807 images.

The model was trained for 50 epochs on both versions of the dataset separately. The default learning rate was 0.001, and the batch size was 32. The Adam (Adaptive Moment Estimation) optimizer was utilized to facilitate convergence and minimize the loss function.

## 5.2 Performance Metrics

**Accuracy:** The ratio of correctly identified positive samples to the total number of anticipated positive samples is known as accuracy.

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative} \tag{5.1}$$

**Precision:** The ratio of correctly identified positive samples to the total number of projected positive samples is known as precision.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \tag{5.2}$$

**Recall:** The recall can be defined as the percentage of all correctly identified positive samples that were appropriately recognized..

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \tag{5.3}$$

**F1-Score:** The weighted average of precision and recall combined into a single value is called the F1 score.

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{5.4}$$

## 5.3 Results and Analysis

The proposed model achieves the highest classification accuracy of 99.29% on the Fruit-360 dataset with 131 categories and 99.25% on the Fruit-360 dataset with 81 categories. These findings show that our suggested model has a great deal of potential and beats the most advanced models for Fruit-360 categorization. Table 5.1 shows the accuracy obtained by the proposed model on the Fruit-360 test dataset with 81 categories and Fruit-360 test dataset with 131 categories.

Table 5.1: Classification results

| **Dataset** | **No. of Test Images** | **Testing Accuracy** | **Testing Loss** | **Total no. of Parameters** |
|---|---|---|---|---|
| Fruit-360 81 category | 4164 | 99.25% | 0.041 | 34,254 |
| Fruit-360 131 category | 6807 | 99.29% | 0.062 | 49,754 |

The training and validation accuracy and loss for the 131-category Fruit-360 dataset are shown in Figure 5.1 for each epoch. Similarly, with the Fruit-360 dataset with 81 categories, Figure 5.2 shows the accuracy and loss during training and validation for each epoch. A comparison of the suggested model's classification accuracy with that of the baseline ”PCNN model” is shown in Table 5.2. On the Fruit-360 dataset, Table 5.3 displays the classification accuracy attained by alternative cutting-edge methods.

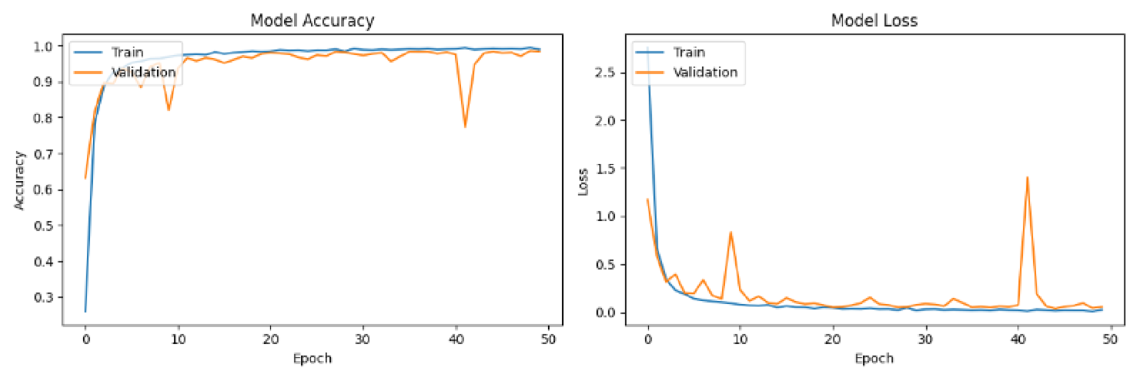


Figure 5.1: Accuracy and loss at each epoch for Fruit-360 81 category

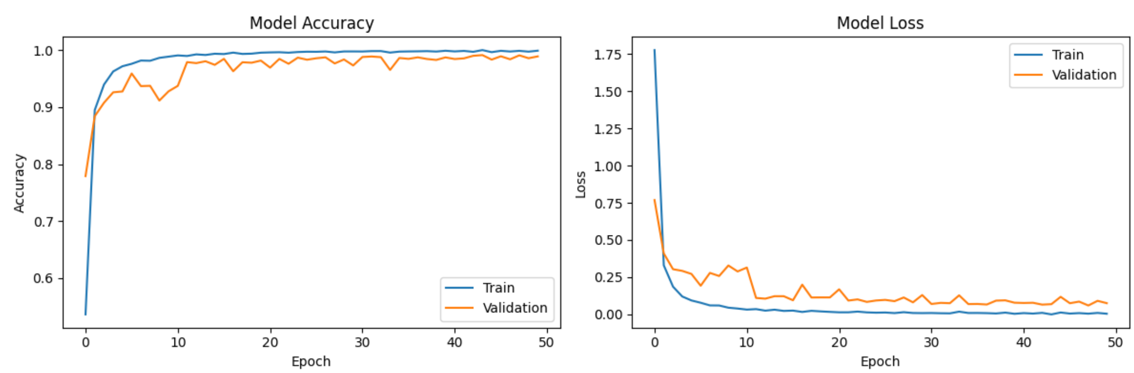


Figure 5.2: Accuracy and loss at each epoch for Fruit-360 131 category

Table 5.2: Comparision of classification with base model

| **Model Name** | **No. of Test Images** | **Testing Accuracy** | **No. of Wrong Predicted** | **Total no. of Parameters** |
|---|---|---|---|---|
| PCNN+GAP on 81 category | 4133 | 98.88% | 46 | 95,817 |
| Proposed Model on 81 category | 4164 | 99.25% | 31 | 34,254 |
| Proposed Model on 131 category | 6807 | 99.29% | 48 | 49,754 |

Table 5.3: Classification comparison with cutting-edge models

| **Paper Name** | **Model Used** | **Dataset Used** | **Samples** | **Accuracy** |
|---|---|---|---|---|
| (1) Fruit Image Classification Model Using Deep Transfer Learning Technique and Based on MobileNetV2 (2023) | TL-MobileNet-V2 | Fruit-360 40 category | 27,000 | 99% |
| (2) Classification of Fruits and Vegetables using ResNet Model (2021) | ResNet Pretrained Model | Fruit-360 131 category | 67,692 | 95.83% |

| | | | | |
|---|---|---|---|---|
| (3) A New Modified CascadedANFIS Algorithm for Effective Automatic Fruit-360 Image Identification and Recognition (2022) | Cascaded-ANFIS Model | Fruit-360 131 category | 67,692 | 98.36% |
| (4) Transfer Learning for Fruit Recognition Using an Efficient Convolutional Neural Network (2019) | Customized MobileNet | Fruit-360 81 category | 55,244 | 98.06% |
| (5) Fruit Classification Using Attention Mechanism and ResNet (2023) | ResNet and Attention Model | Fruit-360 131 category | 67,692 | 98% |
| (6) New Developments in Deep Learning-Based Fruit Detection and Classification (2022) | ResNet-50 | Fruit-360 120 category | 60,498 | 99% |
| (7) Research on Fruit Category Classification Based on Convolution Neural Network and Data Augmentation (2019) | IANet (Optimizing AlexNet) | Fruits-360 74 category | 49,561 | 98.06% |

Confusion matrices were produced in order to classify the two datasets. These matrices offer comprehensive insights into the classification performance, displaying individual examples of true positives, true negatives, false positives, and false negatives in addition to the overall accuracy. The aforementioned measures facilitate a more profound comprehension of the model's merits and demerits in distinguishing various fruit groups. The suggested model's overall precision, recall, and f1 score for the two datasets are displayed in Table 5.4. Figure 5.3 represents the confusion matrix over Fruit-360 81 category dataset and Figure 5.4 represents the confusion matrix over Fruit-360 131 category dataset. Figure 5.5 shows the predicted sample results on 12 test images by proposed classification model.

Table 5.4: Overall Precision, Recall, and F1 score

| **Dataset Used** | **Precision** | **Recall** | **F1 Score** |
|---|---|---|---|
| Fruit-360 131 category | 0.9949 | 0.9945 | 0.9943 |
| Fruit-360 81 category | 0.9924 | 0.9923 | 0.9923 |

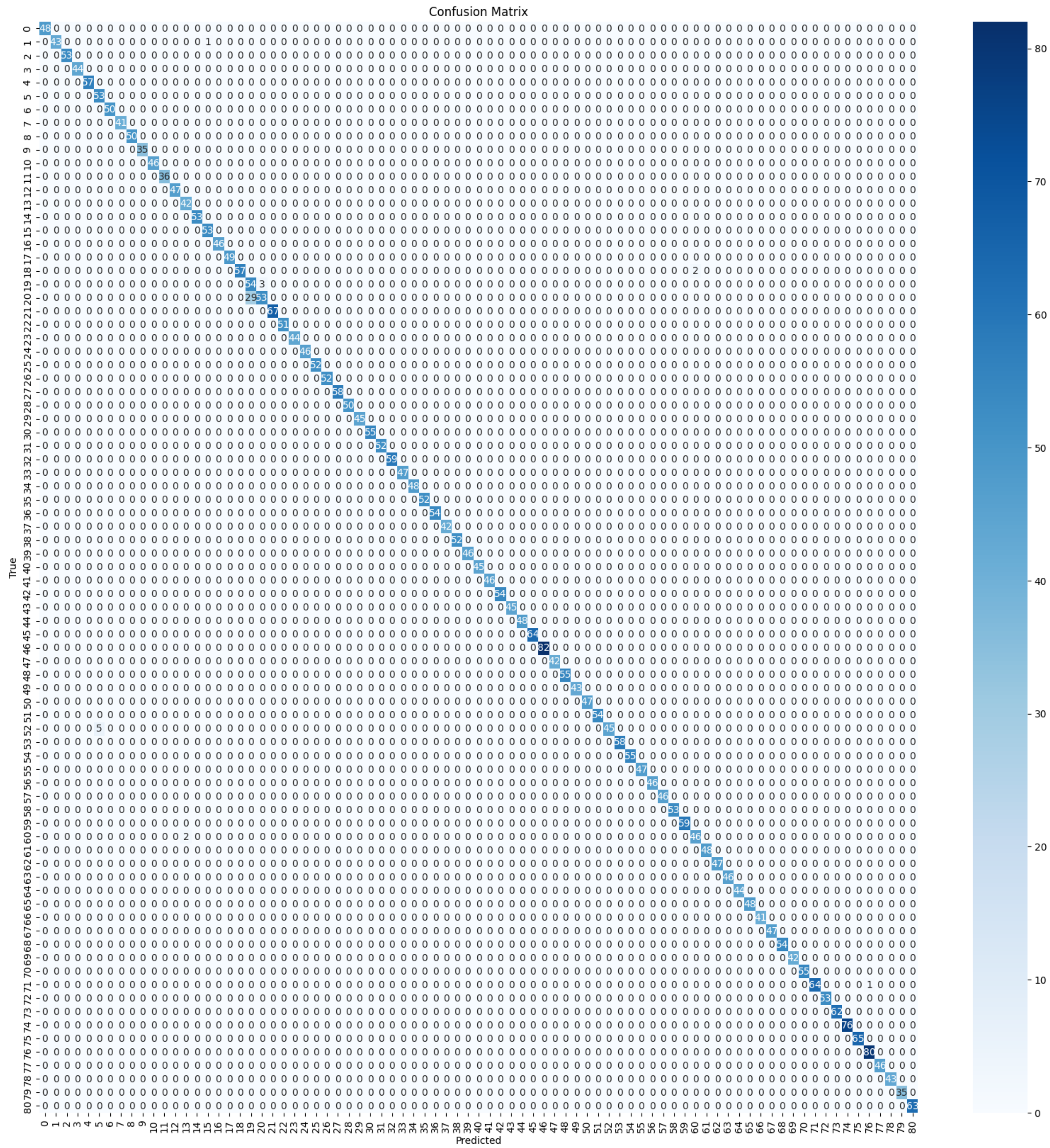


Figure 5.3: Confusion matrix of Fruit-360 81 category

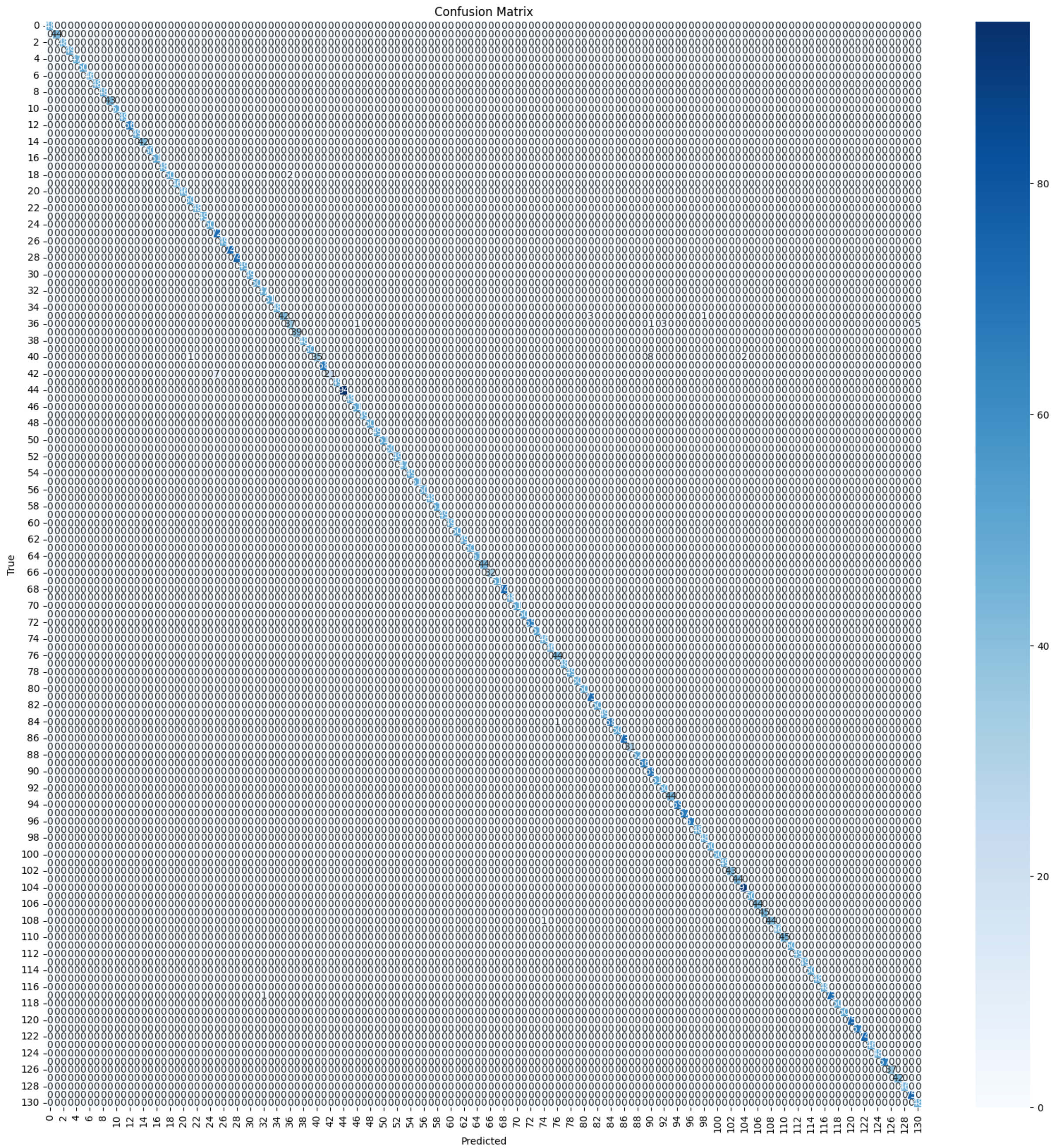


Figure 5.4: Confusion matrix of Fruit-360 131 category

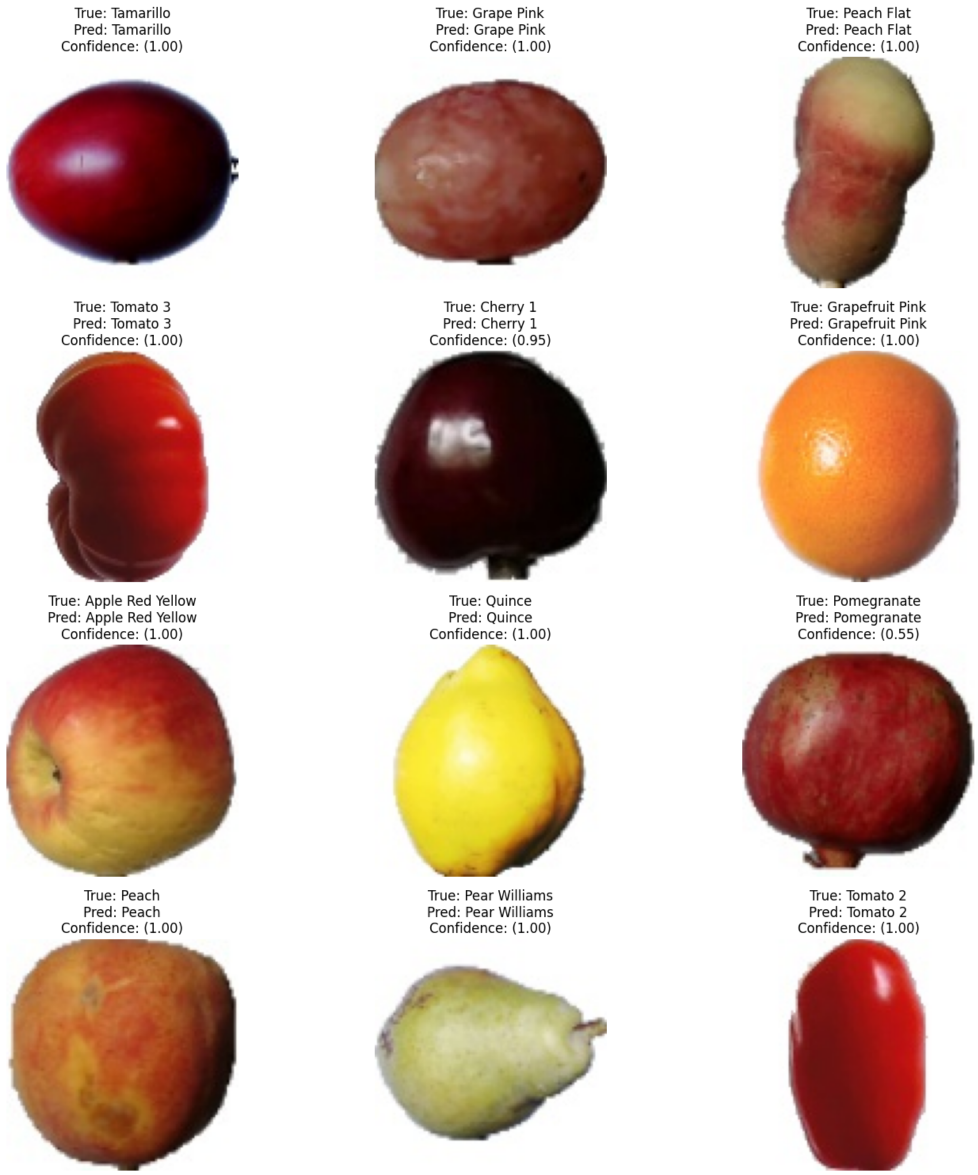


Figure 5.5: Sample results of proposed classification model

# Chapter 6

# Conclusion and Future Work

The proposed model "Depthwise Separable Convolution with Learnable Weighted Skip Connections" presents an innovative and efficient approach for automated fruit classification. By leveraging Depthwise Separable Convolutions, the model significantly reduces the number of parameters and computational complexity, making it suitable for deployment on devices with limited resources, such as mobile phones. The inclusion of Global Average Pooling (GAP) and Learnable Weighted Skip Connections further enhances the model's ability to learn and generalize from the data, preventing overfitting and improving classification accuracy.

The model performs quite well, as evidenced by our testing findings on the Fruit-360 dataset, which show 99.25% classification accuracy on the first version and 99.29% on the second. The model's efficiency and great accuracy make it a useful tool for real-world agricultural applications. The deployment on the Hugging Face platform ensures scalability and ease of access, while the integration into an Android app provides users with a convenient, real-time fruit classification tool. This project addresses the limitations of existing fruit classification systems by offering a solution that is not only accurate and efficient but also accessible and scalable.

While the proposed model demonstrates significant advancements in fruit classification, there are several areas for future research and development to further enhance its capabilities. One potential area is the expansion to other datasets. Training and testing the model on a wider variety of datasets, including those with different fruit types, backgrounds, and lighting conditions, will improve the model's robustness in diverse real-world scenarios. Incorporating additional features such as fruit ripeness detection or defect identification can also add significant value to the classification system. By training the model to recognize and classify these additional attributes, the system could provide more comprehensive information about the fruits, aiding in better quality control and decision-making processes. This enhancement would make the classification system more useful and practical for farmers and other stakeholders in the agricultural industry. By focusing on these areas, the proposed system can be further refined and expanded, providing a more comprehensive, efficient, and practical tool for the agricultural sector. The continued evolution of this technology holds great promise for advancing smart agricultural practices and improving overall productivity and sustainability.

# References


1. A. Kausar, M. Sharif, J. Park, and D. R. Shin, "Pure-CNN: A Framework for Fruit Images Classification," in Proceedings of the 2018 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, December 2018.

2. N. Rathnayake, U. Rathnayake, T. L. Dang, and Y. Hoshino, "An efficient automatic Fruit-360 image identification and recognition using a novel modified cascaded-ANFIS algorithm," School of Systems Engineering, Kochi University of Technology, vol. 1, no. 1, pp. 1–10, 2023.

3. Z. Huang, "Transfer Learning with Efficient Convolutional Neural Network for Fruit Recognition," in Proceedings of the 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Chengdu, China, pp. 1-6, 2019.

4. M. Lin, "Fruit Classification based on ResNet and Attention Mechanism," Highlights in Science, Engineering and Technology CSIC 2022, vol. 34, pp. 163-170, 2023.

5. C. C. Ukwuoma, Q. Zhiguang, M. B. B. Heyat, L. Ali, Z. Almaspoor, and H. N. Monday, "Recent Advancements in Fruit Detection and Classification Using Deep Learning Techniques," in Proceedings of the 2022 IEEE 4th International Conference on Computer Science, Information Technology, and Automation (CSITA), Chengdu, China, pp. 1-6, 2022.

6. D. Zhu, M. Wang, Q. Zou, D. Shen, and J. Luo, "Research on Fruit Category Classification Based on Convolution Neural Network and Data Augmentation," in Proceedings of the 2022 International Conference on Advanced Computational Intelligence (ICACI), Ganzhou, China, pp. 1-6, 2022.

7. M. Dandekar, N. S. Punn, S. K. Sonbhadra, and S. Agarwal, "Fruit Classification Using Deep Feature Maps in the Presence of Deceptive Similar Classes," in Proceedings of the 2022 IEEE International Conference on Data Science and Advanced Analytics (DSAA), Prayagraj, India, pp. 1-6, 2022.

8. H. Mureșan and M. Oltean, "Fruit recognition from images using deep learning," Acta Univ. Sapientiae, Informatica, vol. 10, no. 1, pp. 26–42, 2018.

9. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, pp. 770-778, 2016.

10. F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, pp. 1251-1258, 2017.

sumanta

ORIGINALITY REPORT

| 9% | 4% | 6% | 4% |
|---|---|---|---|
| SIMILARITY INDEX | INTERNET SOURCES | PUBLICATIONS | STUDENT PAPERS |

PRIMARY SOURCES

| | | |
|---|---|---|
| 1 | Teena Varma, Prajwal Mate, Noamaan Abdul Azeem, Sanjeev Sharma, Bhupendra Singh. "Automatic mango leaf disease detection using different transfer learning models", Multimedia Tools and Applications, 2024<br>Publication | 1% |
| 2 | dokumen.pub<br>Internet Source | 1% |
| 3 | Ruizhen Liu, Zhiyi Sun, Anhong Wang, Kai Yang, Yin Wang, Qianlai Sun. "Real-time defect detection network for polarizer based on deep learning", Journal of Intelligent Manufacturing, 2020<br>Publication | <1% |
| 4 | www.mdpi.com<br>Internet Source | <1% |
| 5 | arxiv.org<br>Internet Source | <1% |
| 6 | Submitted to National College of Ireland<br>Student Paper | <1% |

| | | | |
|---|---|---|---|
| 7 | Submitted to University of Technology, Sydney<br>Student Paper | <1 % |
| 8 | wiredspace.wits.ac.za<br>Internet Source | <1 % |
| 9 | Chintan Chatterjee, Nihir Shah, Sahil Bhatt, Smit Chandi. "A Survey on Multi-modal Emotion Detection Techniques", Research Square Platform LLC, 2024<br>Publication | <1 % |
| 10 | plantmethods.biomedcentral.com<br>Internet Source | <1 % |
| 11 | Chen Guo, Haipeng Wang, Tao Jian, You He, Xiaohan Zhang. "Radar Target Recognition Based on Feature Pyramid Fusion Lightweight CNN", IEEE Access, 2019<br>Publication | <1 % |
| 12 | gupea.ub.gu.se<br>Internet Source | <1 % |
| 13 | Ali Al Bataineh, Sarah Manacek. "MLP-PSO Hybrid Algorithm for Heart Disease Prediction", Journal of Personalized Medicine, 2022<br>Publication | <1 % |
| 14 | ijritcc.org<br>Internet Source | <1 % |

| | | |
|---|---|---|
| 15 | Submitted to The Robert Gordon University<br>Student Paper | <1% |
| 16 | Submitted to University Tun Hussein Onn Malaysia<br>Student Paper | <1% |
| 17 | Submitted to Colorado Technical University<br>Student Paper | <1% |
| 18 | Submitted to Hamdan Bin Mohammed Smart University<br>Student Paper | <1% |
| 19 | Submitted to Imperial College of Science, Technology and Medicine<br>Student Paper | <1% |
| 20 | deepai.org<br>Internet Source | <1% |
| 21 | Umesh Kumar Lilhore, Surjeet Dalal, Sarita Simaiya. "A Cognitive Security Framework for Detecting Intrusions in IoT and 5G Utilizing Deep Learning", Computers & Security, 2023<br>Publication | <1% |
| 22 | Wei Chen, Qiang Sun, Jue Wang, Jing-Jing Dong, Chen Xu. "A Novel Model Based on AdaBoost and Deep CNN for Vehicle Classification", IEEE Access, 2018<br>Publication | <1% |
| 23 | downloads.hindawi.com<br>Internet Source | |

<1 %

24 raiith.iith.ac.in
Internet Source
<1 %

25 Khashayar Asadi, Pengyu Chen, Kevin Han, Tianfu Wu, Edgar Lobaton. "Real-Time Scene Segmentation Using a Light Deep Neural Network Architecture for Autonomous Robot Navigation on Construction Sites", Computing in Civil Engineering 2019, 2019
Publication
<1 %

26 Mathew, Jacob. "Methodology to Estimate Crash Frequency at Highway-Rail Grade Crossings in a Connected Vehicle Environment", University of Illinois at Urbana-Champaign, 2024
Publication
<1 %

27 Ravindranath, Manjusha. "Metadata Supported Multi-Variate Multi-Scale Attention for Onset Detection and Prediction", Arizona State University, 2024
Publication
<1 %

28 uri.gbv.de
Internet Source
<1 %

29 Jia-Hong Lee, Yi-Ming Chan, Ting-Yen Chen, Chu-Song Chen. "Joint Estimation of Age and Gender from Unconstrained Face Images
<1 %

Using Lightweight Multi-Task CNN for Mobile Applications", 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), 2018
Publication