FRUIT QUALITY AND DEFECT CLASSIFICATION USING DEEP LEARNING

A DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENTSFOR THE AWARD OF THE DEGREE

OF

MASTER OF TECHNOLOGY

IN

SIGNAL PROCESSING AND DIGITAL DESIGN

Submitted by:

Avaneesh Kumar

2K22/SPD/02

Under the supervision of

Prof. O. P. Verma

(Prof. ECE Dept.)

DEPARTMENT OF ELECTRONICS AND COMM ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

MAY, 2024

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College Engineering)

Bawana Road, Delhi-110042

CANDIDATE'S DECLARATION

I, Avaneesh Kumar, Roll No. 2K22/SPD/02 student of MTech (Signal Processing and DigitalDesign), hereby declare that the project Dissertation titled **"Fruit Quality And Defect Classification Using Deep Learning"** which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological university, Delhi in partial fulfillment ofthe requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship, or other similar title or recognition.

Place: Delhi — Avaneesh Kumar

Date: — (2K22/SPD/02)

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

CERTIFICATE

We hereby certify that the project Dissertation titled **"Fruit Quality And Defect Classification Using Deep Learning"** which is submitted by Avaneesh Kumar, Roll No. 2K22/SPD/02, Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology,is a record of the project work carried out by the students under our supervision. To the best of our knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi **SUPERVISOR**

Date: Prof. O. P. Verma

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

ACKNOWLEDGEMENT

I would like to express my gratitude towards all the people who have contributed their precious time and effort to help me without whom it would not have been possible for me to understand and complete the project. The VGG16 model was fine-tuned, aiming to optimally classify lemon quality based on 2,690 categorized lemon images from a publicly available dataset. This enabled huge hyperparameter tuning, allowing data augmentation both of which significantly improved model accuracy and, hence, generalization. We appreciate the provider of this dataset; without their support, such a great leap would be impossible in the quality assessment of lemons.

I would like to thank Prof. O. P. Verma, DTU Delhi, Department of Electronics and Communication Engineering, my Project supervisor, for supporting, motivating, and encouraging me throughout the period this work was carried out. Their readiness for consultation at all times, their educative comments, their concern, and their assistance even with practical things have been invaluable.

Date :

Place:

Avaneesh Kumar

M. Tech(SPDD)

Roll No.- 2K22/SPD/02

ABSTRACT

Agriculture emphasizes the need to automate quality improvement and enable uniform defect classification due to high efficiency for that matter. This is particularly due to the cases of inefficient practices notable in the procedures now in place. According to this thesis, we assert an innovative approach introducing the application of the YOLOv7 deep learning model to automate the process of identifying defects and classifying quality in fruits with around 88% accuracy. The YOLOv7 model, which is effective in object detection and subsequent classification, has been optimized to detect a wide range of fruits. This is critical in ensuring that the evaluations can be uniform hence trustworthy. Moreover, the model training time has been reduced using simpler computers hence more feasible when handling many data. This project draws data from many fruits to ascertain different quality ranges. Therefore, the project utilizes deep learning approaches including Convolutional Neural Networks to identify and learn essential features from the images. With extensive training and validation, which sometimes includes data expansion, the model is significantly enhanced for its generalization and robustness. Quality assessment using the YOLOv7 model in automation reflects considerable gain. The model has a practical implementation with an accuracy level of around 79.6%. The model minimizes errors and enhances uniform evaluation by reducing the dependence on manual workers. Farm input will, thus, experience high output through this automation system with low entry and economic results.

TABLE OF CONTENTS

CHAPTER 3

BACKGROUND TECHNIQUES

CHAPTER 4

PROPOSED METHODOLOGY

CHAPTER 5

EXPERIMENTAL RESULTS

CHAPTER 6

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

YOLO	You Only Look Once
FPS	Frames Per Second
CNN	Convolutional Neural Network
SPP	Spatial Pyramidal Parsing
Conv	Convolution
GPU	Graphics Processing Unit
TPU	Tensor Processing Unit
RNN	Recurrent Neural Network

CHAPTER 1
INTRODUCTION

1.1 Overview of Fruit Quality Assessment

Fruit quality evaluation is a multi-dimensional process that primarily focuses on the overall condition of the fruits and their suitability for processing, consumption, or even marketing. An evaluation of physical, chemical, and sensory attributes touches on features indicating, apart from others, freshness, maturity, taste, nutritional value, and aesthetic quality. In agriculture, the assessment [1] of fruit quality usually begins with an on-site examination of primary indicators of the fruit's health and maturity, such as size, shape, color, and external blemishes. The next steps might be the conduction of more sophisticated measurements such as firmness, content of sugars (Brix), acidity levels (pH), and aroma with the help of non-destructive tests by using spectroscopy and imaging or electronic nose technologies.

Moreover, apart from the stated basic parameters, the modern fruit quality assessment is based on the implementation of techniques, among which the most important are chromatography, mass spectrometry, and near-infrared spectroscopy techniques intended for the quantitative assessment of biochemical composition and detection of trace amounts of contaminants or adulterants. So, not only do they allow for the detection [2] of a set of ingredients, i.e., antioxidants, vitamins, pesticides, or pathogens, but also allow for information about nutritional values, safety, or shelf life predictions to be provided.

On the other hand, the sensory evaluation techniques: descriptive analysis, consumer preference testing, and trained panel evaluation are taken into use to deal with the subjective attributes of taste, texture, juiciness, and overall acceptability.

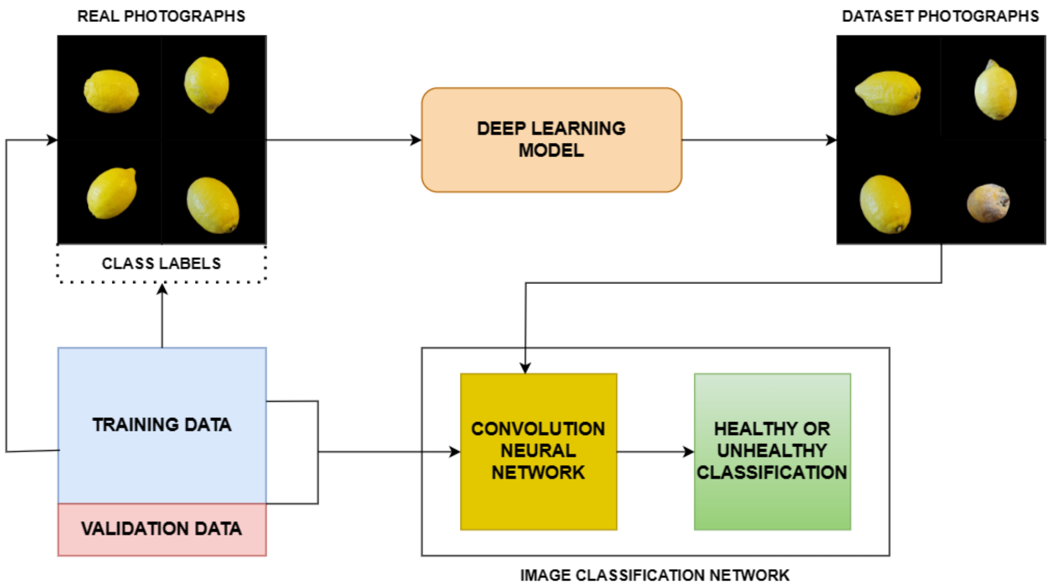

Figure 1.1 A general overview of our proposed approach

Now, these techniques build human perception within the frame of fruit quality assessment; hence, objective measurements are tuned with the consumer's expectation and the market's preference. On the commercial scale, fruit quality [3] assessment forms an integral part of quality control and assurance programs for producers, processors, and distributors to maintain the variegated facets of consistency, compliance, and competitiveness in both domestic and international markets. It is maintained at all costs up to the required standards of quality between farm and fork in such a way that it ensures the health and satisfaction of the consumer, and simultaneously builds trust, brand loyalty, and market differentiation in an industrial landscape that is increasingly demanding and competitive.

1.2 Issues in Fruit Quality Assessment

By the same token, traditional frameworks face several problems in the context of assessing fruit quality. Quality assessment processes are, by nature, subjective and, therefore, lack repeatability, particularly when their attributes are subjective characteristics like taste and texture. Also, while visual inspection informs as to surface defects, low potential to assess intrinsic or internal quality parameters like sugar content or the presence of microorganisms is there. Further, the results of manual sorting and grading are laborious, tedious, and intensive resource-wise, with poor scalability in high-throughput production environments.

Apart from the above, sensory evaluation also has problems of biases and inter-assessor variability. The process of multi-attribute evaluation is complex and further requires methodologies of high-end analysis. Defects like internal bruising or even pesticide residues remain invisible and undetectable through conventional methods, hence a potential source of risk for the health of the consumer and the integrity of the product. Small inconsistencies in protocols from region to region and amongst organizations lead to differences in the quality of the grading. Further, advanced analytical technologies are not well inducted because of their high cost and limited resources for smaller producers. Life cycle real-time monitoring, by way of its logistic challenges, is tantamount to a strong tracking and surveillance system to ascertain quality standards for product safety in the supply chain. There is, therefore, a need for innovative solutions of efficiency, accuracy, and objectivity in the procedures for the assessment of fruit quality to enhance the quality, safety, and market competitiveness of the product.

1.3 Importance of Addressing Challenges in Fruit Quality Assessment

It can be said that conquering the identified challenges can be the key directly to impacting the different sub-sectors in agriculture, food processing, and retail industries. Reliable quality standards are fundamental in the interest of consumer health, operation efficiency, international trade, and innovation. Objective assessment methods are critical at the forefront of overcoming subjectivity and inconsistency of quality evaluation. Advanced analytical techniques, using spectroscopy and chromatography, coupled with automated grading systems go a long way in reducing human bias and significantly increasing the accuracy and reproducibility of assessments.

In addition, there is a need to increase the precision of quality assessment in detecting and managing risks to consumers. Conventional methods are unreliability since they cannot detect concealed defects and/or contaminants. Such undermines public health and brand value. The use of advanced detection technologies and strict quality control will be crucial in the capability of pinpointing and managing sources of risk for consumer welfare and regulatory compliance. It is essential to standardize protocols within regions and sectors in quality evaluation. Easily accessible standardized guidance and protocols reduce market access time and simplify interoperability, fostering international cooperation that will be beneficial to both producer and consumer or processor. This eventually focuses on innovation and technological development in the fields of agriculture and food. Investment in research and development work for overcoming already existing limitations leads to new opportunities in value addition, product differentiation, and market expansion, which sustain growth and competitiveness. From the above points, it is obvious that the quality evaluation of fruit surely puts the assurance and competitiveness of the product at the orchard to the retail level. Therefore, it is only through collective efforts to integrate innovations, standardization, and cooperation that these stakeholders are likely to overcome these challenges and harness the potential of the fruit industry.

1.4 Advancements in Fruit Quality Assessment Technologies

The last years have seen a great boost of technologies for fruit quality assessment with the progress of innovative sensor technology, data analytics, and machine methodologies on top. Broadly speaking, such developments promise great opportunity for the issues more commonly observable in present-day fruit quality evaluation methods and hence promise the possibility of better accurate, efficient, and objective processes of evaluation. A great deal of this umbrella of technological advances includes the following: Advanced sensor technologies have been developed that can capture a large amount of information and characteristics belonging to a fruit under high resolution and high detail. The use of hyperspectral imaging can provide detailed spectra of the fruit, thus giving out information about its biochemical composition, state, ripeness, and structural integrity. Upon this, the means for acoustic resonance and impedance spectroscopy methods for fruit firmness, density, and internal characterization are explained, and lastly, in line with advanced sensor techniques, there is provision for the use of advanced data analytics methods—both machine learning and statistical modeling—for extraction of valuable information from complex, multi-view datasets. In a general sense, this applies to the technology of deep learning, in an automated fashion, to learn complex patterns and features from large-scale data, likewise, enhancing the accuracy and robustness of the fruit quality assessment models. The deep neural network architecture in the form of convolutional and recurrent neural networks yields a very powerful tool for analyzing diverse data modalities like images, spectral profiles, and text descriptions for fruit classification[4] and defect detection.

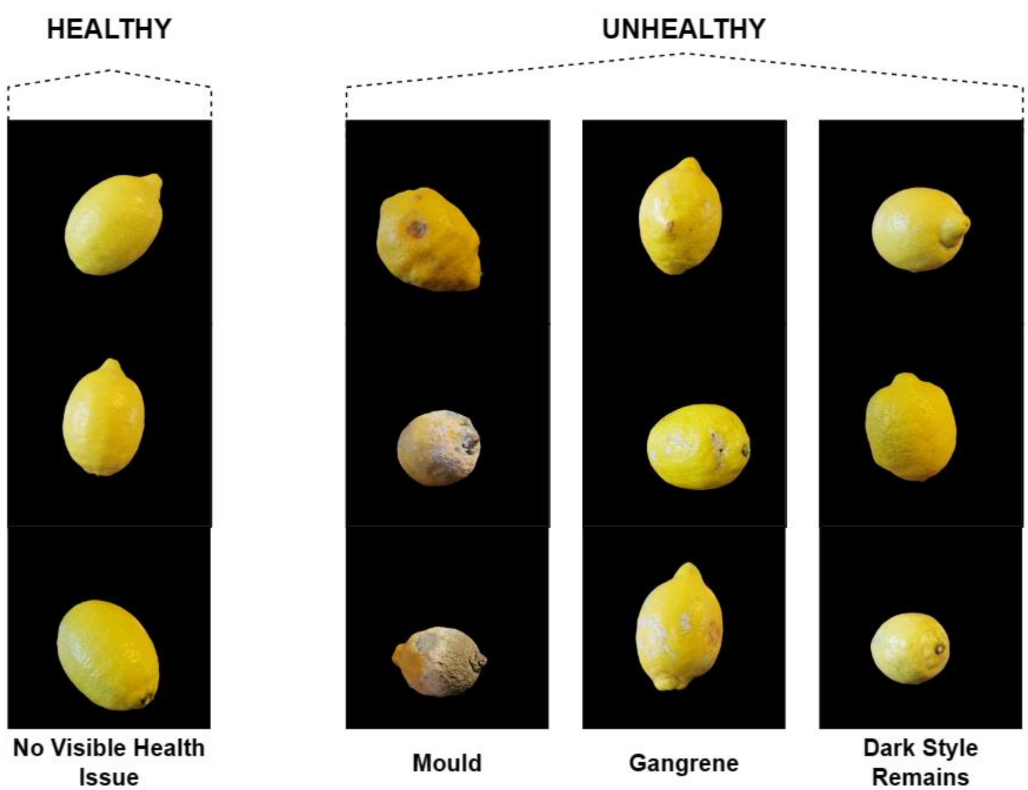

Figure 1.2 Visualization of healthy and unhealthy lemons (mouldy, gangrenous, and those with a dark style remaining are all considered unhealthy).

Meanwhile, ensemble methods and fine-tuning are advanced techniques that significantly increase the ability to generalize deep learning models and their performance, especially in data-limited and few-shot scenarios of labeled data, due to processes of training and inference of deep learning models that are much faster on accelerated hardware technologies, such as GPUs and TPUs, making these processes accessible and scalable in practice for fruit quality assessment. Data analytics, sensor technologies, and machine-learning methodologies have fully come together to develop new novelties in assessing the quality of fruits [5], and all of them jointly hold great promise for further improvement in the efficiency, accuracy, and objectiveness of the fruit-quality-evaluation process, translating into the gain of all stakeholders across the entire fruit supply chain.

1.5 Potential Applications of Deep Learning in Fruit Quality Assessment

Also, deep learning, a branch of machine learning, holds the potential for revolutionizing the determination of fruit quality since it automatically learns the details of patterns and features within often highly unstructured and noisy datasets. In this regard, using deep neural networks, such as convolutional neural networks [6] (CNNs) and recurrent neural networks (RNNs, researchers and practitioners, have managed to build models with increasing complexity that can derive meaningful information from multimodal data, which is very common in fruit quality assessment. One of the most common applications of DL in the context of fruit quality inspection is image-based classification and defect detection.

By training a CNN on the widely available and accessible large datasets of fruit images, with annotations of quality attributes and defects, it, in turn, can follow classification tasks coming from the ripeness, size, shape, color, and texture of the fruits, and resist to common defects such as bruising, blemishes, and mold. In this context, hierarchical feature learning of CNNs allows identifying subtle visual cues indicative of the fruits' quality even if accompanied by noise and variations. Other types of data that could be analyzed with deep or other DL techniques are spectral data obtained by techniques like hyperspectral imaging or spectroscopy. Therefore, CNNs built for other types of neural network structures can analyze the spectral profiles to define characteristic absorption patterns associated with some biochemical compounds or quality markers in the fruits. This leads to non-destructive, fast fruit freshness testing, measuring sugar content, acidity, or other chemical features of fruits, which directly emails the grading and sorting of fruits. In addition, the models based on deep learning can deploy different sources of multimodal data—in this case, images, spectral signatures, or textual descriptions—to allow comprehensive assessments of the quality of fruits. Such models can then integrate information from multiple sources to encapsulate complementary information and improve the overall accuracy and reliability of such quality assessments.

For example, the fusion of extracted image visual features [7] with spectroscopic measurements in terms of spectral signatures allows a more integrated characterization of fruit properties and defects. Moreover, the employed deep learning techniques are easily adaptable to new fruit quality detection tasks. They can work in the online mode within the process of detecting fruit quality. The most important advantage of the deep learning-based approaches is the scalability and adaptability of the models toward their successful deployment for real-time monitoring and decision-making applications in quality assessment of different fruits. These models can be applied in practice by any stakeholders using edge devices or embedded system solutions, including IoT sensors and smart cameras capable of performing on-site quality inspection and sorting optimization to ensure the freshness and safety of products in the whole supply chain. In conclusion, deep learning can be extensively applied across image-based classification and defect detection to spectral analysis and multimodal fusion for fruit quality assessment. Deep neural networks provide on one side opportunities for the stakeholders to enhance the efficiency, accuracy, and robustness of the fruit quality evaluation process and on the other side enhance the delivered product quality, satisfaction of the consumer, and competitiveness in the market.

1.6 Challenges and Opportunities in Implementing Deep Learning for Fruit Quality Assessment

This, on the one hand, illustrates a set of challenges and opportunities for implementing deep learning techniques into practice as these technologies feature promising capabilities for increasing the efficiency and precision of quality evaluation processes. In practice, though, their implementation would first require clearing several technical, logistic, and operational hurdles. The problems herein are related to data scarcity during deep learning model training. The annotation of such large datasets capturing such diversity of fruit types and defect classes using labor-intensive and time-consuming processes has been quite prohibitive in terms of resources and time.

The other, most important fact to take into account is maintaining the correctness and consistency of the annotations to robustly train models that will generalize to new data. These efforts have to be collaborative between researchers, industrial partners, and data providers to target the issues of data scarcity that directly support the development of high-quality training datasets. Deep neural networks are often treated as black-box models, and it is very challenging to grasp the interpretation of the inner decision-making processes to understand sources of potential error or bias. Deep model interpretability and the development of uncertainty estimation are crucial to assure acceptance—in this case, before industry—which the decisions a deep learning-based quality evaluation system will take. In addition, deep learning, in principle, is computationally and infrastructure-intensive, raising practical problems for deploying such methods in real-world scenarios. The training of such complex or deep neural networks on large datasets is considerably computationally intensive and requires heavy computational resources, such as high-performance computing clusters or cloud-based infrastructure. Besides, the deployment of trained models on embedded or edge systems, whose processing power and memory are generally limited, has further constraints that need enforcement by optimization and model.

These challenges notwithstanding, deep learning in fruit quality assessment holds huge potential for innovation and growth. In this regard, one can work on a solution to fruit quality assessment by using transfer learning, domain adaptation, and semi-supervised learning to circumvent issues linked with data scarcity and make the development of models faster. Furthermore, such software and framework improvements, supported by hardware level acceleration, make deep learning models computationally more efficient and hence practically more feasible in a real-world scenario. Moreover, modular and flexible architectures support customization and reconfiguration of these architectures for peculiar cases and requirements. Therefore, deep learning researchers and practitioners have the opportunity to formulate deep learning architectures, loss functions, and optimization strategies by the unique characteristics and constraints brought about by the tasks of fruit quality assessment.

On the other hand, the rapid evolution of deep learning research projects, accompanied by interdisciplinary cooperation, opens a new frontier in solving highly complex challenges and unlocking newer capabilities with fruit quality assessment. In a nutshell, the application of deep learning in fruit quality assessment produces a myriad of predicaments but is equally promising regarding innovation and growth. In effect, the advancement in algorithmic techniques and hardware technologies, specifically addressing issues related to data scarcity, interpretability, and infrastructure constraints, is further raised to unlock the full potential of deep learning for the enhancement of efficiency, accuracy, and reliability in the evaluation of fruit quality and, in turn, in product quality, safety, and competitiveness in the market.

1.7 DISSERTATION ORGANIZATION

The content of the dissertation is organized into six chapters:

- Chapter I INTRODUCTION TO AUTONOMOUS DRIVING
- Chapter II LITERATURE SURVEY
- Chapter III BACKGROUND TECHNIQUES
- Chapter IV PROPOSED METHODOLOGY
- Chapter V EXPERIMENTAL RESULTS
- Chapter VI CONCLUSION AND FUTURE SCOPE

Chapter I – Includes the introduction of the overview of fruit quality assessment

Chapter II – This chapter is a literature survey, which gives an insight into the research papers published based on object classification, segmentation, and multi-task approaches.

Chapter III – This chapter gives an insight into the background techniques that are being used in the implementation of the proposed work.

Chapter IV – This chapter covers the methodology that includes the classification detection-segmentation architecture of YOLOv7 and system architecture along with the model losses.

Chapter V – This chapter includes the experimental results. The results also involve the performance of YOLOv7 and CNN.

Chapter VI – This includes the conclusion about the research work and future scope.

CHAPTER 2

LITERATURE SURVEY

Quality assessment of fruits and classification of fruit defects are key operations in food and processing agro-based enterprises to ensure consumer satisfaction, product safety, and market competitiveness. Conventional methods for the measurement of fruit quality and classification of defects mainly depend on hand inspection and subjective judgment; hence they are bound to be irrational and unstable during the process of quality evaluation. The application of deep learning methods in this revolution was analyzed in this study. Several investigations about the application of deep learning methods focused on automated assessment, especially using the convolutional neural networks for fruit classification through visual appearance data described by size, shape, color, and surface defects. Trained with a large number of annotated image datasets, CNNs can produce quality labels, and in most cases, such networks produce high-quality and robust results compared to traditional methods and human experts.

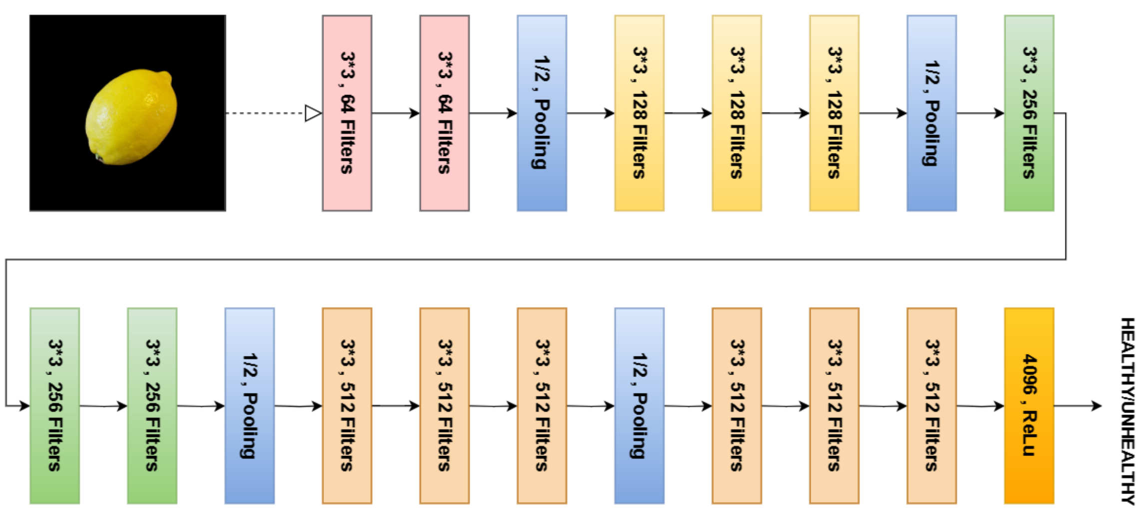

Figure 2.1 custom interpretation and output layer which is used for binary image classification

Data science methods have recently gone beyond visual inspection in analyses of other data modalities that one typically encounters in fruit quality assessment, including spectral and chemical composition data. CNNs process spectral profiles to predict the biochemical attributes of fruits, while RNNs crunch real-time time-series sensor data during the storage and transportation of fruits for quality monitoring [8]. Problems related to data scarcity, high cost of annotation, and interpretability are not solved, so very close multidisciplinary approaches are required when defining real-world standard protocols and validation frameworks.

2.1 Advancements in Fruit Quality Prediction Using Deep Learning Algorithms

Here we report a pioneering approach to predicting fruit quality based on state-of-the-art deep-learning methodologies. Fruit quality assessment traditionally has been labor-intensive and subjective through manual inspection techniques. Deep learning, particularly using convolutional neural networks, automates extraction [9] from images of characteristics associated with fruits, making the process much faster and more objective. Since CNNs enable the recognition of complex visual patterns, it is possible to predict the maturities of fruits in a precise and scalable way, leading to superior efforts in guiding harvesting decisions toward optimal timings at an unprecedented level of accuracy.

Moreover, if RNNs are added, non-destructive fruit quality assessment may rise to the other level due to the rich tapestry of data inputs and analyses it undertakes. In this way, RNNs excel at decoding the underlying temporal complexities in sequential data, so the essentiality is in understanding the dynamical attributes of fruit quality over time. Bringing together different insights from images, spectral signals, and physical measurements, the RNN-based models offer a holistic vantage of evaluation. The quality prediction fidelity is enhanced with the holistic approach further, which unleashes operations from such labor-intensive and subjective evaluations.

This is because the neural networks on which algorithms based on CNNs and RNNs use large data sets to develop and estimate fruit maturity, quality, and life effects with pinpoint accuracy and completely automated approaches. These provide more operational agility in reducing waste that could support more sustainable and durable economic practices within the food industry. These methodologies would help the agricultural sector to get better, more precise, and more scalable quality appraisals, which would consequently lead to benefits for the producer and consumer.

2.2 Automated Fruit Quality Assessment through Machine Learning

Automation [10] of fruit quality assessment has lately gained a lot of interest and seems to be a productive, quick, and innovative evaluation method useful to agriculture and the food industry. Current manual inspection methods for fruit quality evaluation are highly subjective, inconsistent, and labor-intensive. With the rise of machine learning, in particular deep learning, automation of quality assessment has also conducted a revolution in the ability to develop and train algorithms for fruit quality analysis from images. It is shown that a lot of effort has been put towards building a fruit-dedicated machine learning model for the task of quality assessment from images. One of the most widespread is the application of CNNs, as they are outstanding in learning complex patterns and features from large datasets of annotated fruit images. The designed models are required to observe small changes in the features of the fruits, such as color, shape, size, and texture, which enable the classification and quality assessment of the fruit. Therefore, this type of system fused imaging processing with machine learning to improve the efficiency of automated systems for fruit quality assessment.

Most of the preprocessing techniques include feature extraction, image segmentation, and object detection, which play an important role in improving the quality of machine learning models' input data. As such, these preprocessing steps ease the operation of extracting information from regions of interest and help filter the noise so that the focus of the machine learning model is on the relevant aspects of fruit quality, which in turn increases overall accuracy and efficiency. Moreover, the progress made in transfer learning, data augmentation, and model optimization have further impacted the performances and robustness of machine-learning-based fruit-quality assessment systems. For instance, transfer learning enables fine-tuning pre-trained models on smaller, domain-specific datasets that speed up the training and improve generalization on unseen data. Similarly, data augmentation techniques introduce variations into the training data that enrich the generalization ability of the model toward different types of fruits and environmental conditions.

For instance, ongoing studies in model optimization are being driven to expedite the speed and resource efficiency of machine-learning-based models to make them accessible when deployed in real-world settings. How machine learning impacts image-based fruit quality assessment. Machine learning models provide a scalable, objective, and efficient solution to challenges imposed by conventional methods of manual assessment in the automated analysis of images of fruit, through the application of advanced algorithms and techniques. For development in model architectures [11] , data preprocessing techniques, and maybe deployment strategy, research in this area is expected to advance further and will eventually enable wide use of automated fruit quality assessment at work in the agriculture and food industry.

2.3 Advancements in Fruit Quality Assessment Techniques

Fruits are excellent, and their quality assessment has seen breathtaking advancement after the integration of various technologies. Conventional methodologies, based on manual inspection, are being replaced by automated systems, which are empowered by the machine vision and machine learning regimen. The systems show advanced objectivity and are efficient as well as scalable to that of their manual counterparts. Significantly, the use of sophisticated image processing techniques for the extraction of intrinsic features of the fruits and their analysis of color and size attributes.

Machine learning models, for example, support vector machines and artificial neural networks, have greatly contributed to this data to categorize fruits based on quality into different categories with previously unseen accuracy levels. Considering color features as the primary indicators of fruit quality, they have gained maximum attention in modern ways of fruit quality assessment. Features of color are based on color variation, which indicates the ripeness level and physiological changes. The extraction of color features is thus based on color space transformations and histogram-based feature extraction. On the other hand, the size features being based on geometric parameters like length, width, and volume indicate the maturity of the fruits and yield. Researchers are trying to develop the classification models in a robust manner that could help in enabling the differentiation of quality grades of the fruits, including mangoes, based on their color and size characteristics. Therefore, these are attempts in interdisciplinarity: computer vision and machine learning with agricultural sciences trying to bring better practices about quality assessment of fruits in the food industry.

2.4 Technological Advancements in Fruit Categorization and Ripeness Assessment

It is the classification of fruit and its ripeness that has been driven by this recent confluence of advanced methodologies and cutting-edge technologies. Ultimately, the old paradigms do give in to the new powerful frameworks; thus, quite a bit of these strategies are dependent on machine learning optimization algorithms [12] and ensemble modeling, which relies heavily on subjective assessment by human beings or the use of rudimentary color-centric metrics. These frontiers, in turn, struggle to overcome the inherent limitations of traditional methodologies, characterized by a general lack of precision, and provide robust, objective, and data-informed solutions for the evaluation of fruit quality. Based on the latest studies on fruit categorization [13], the emphasis on fusing divergent data modalities, which include the colorimetric, textural, spectral, and biochemical, to form a holistic ripeness assessment framework, has been accentuated.

These frontiers galvanize themselves on account of the utility of ensemble machine learning methods and, in particular, those that use particle swarm optimization to distill the salient inferences from heterogeneous data ensembles, as indicators of higher levels of fidelity and reliability within ripeness classification [14] models. Because of collective intelligence embedded in the ensemble PSO frameworks, the ensemble helps the researcher to optimize the model parameters, bring acceleration in the convergence rate, and enhance the quality of solutions presented in such a way that mission-driven, nuanced, and efficient categorization of fruits can be predicated on ripeness. This work provides a symbiotic amalgamation of interdisciplinary tenets, spreading from the realms of computer vision and optimization theory to agricultural sciences [15], to surmount multifaceted challenges underpinning fruit quality assessment in the industrial landscape of food.

CHAPTER 3

BACKGROUND TECHNIQUES

3.1 ENCODER-DECODER ARCHITECTURES

Encoder-decoder architectures are simple structures that perform feature extraction by generation of feature maps in the first part and detection/segmentation in another part. In the proposed system, the architecture is made up of an encoder component, which is used for processing input sequences of variable length, along with a decoder component—to function as a conditional language model. The encoder takes the input sequence and encoding operations are executed on the same to capture the underlying features. On the other hand, the decoder uses the encoded input and the previous context of the target sequence for target sequence prediction. This dynamic interaction of the encoder and the decoder is used to enable accurate prediction of the next token in the target sequence based on contextual information. YOLOv7 is also an encoder-decoder architecture, where its backbone is the encoder and its head is its decoder.

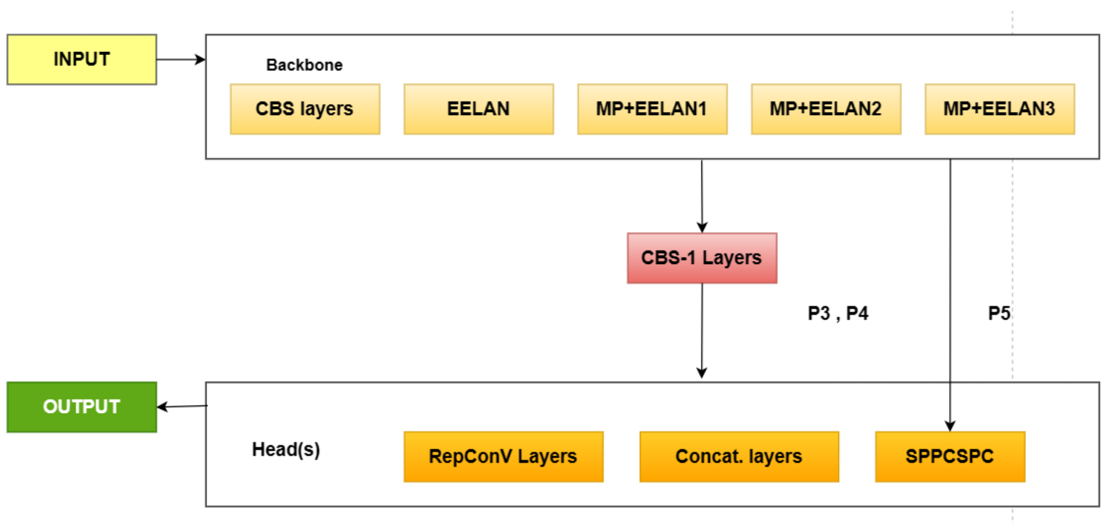

Figure 3.1 An Overview of YOLOv7 Architecture

3.2 Traditional Methods of Fruit Inspection

Traditional methods of fruit inspection have been the cornerstone of fruit quality assessment and defect detection for decades [16]. These methods primarily involve manual inspection, where trained personnel visually examine individual fruits for various attributes such as size, color, shape, and surface defects. While these traditional methods have proven effective to some extent, they are not without their limitations. One of the primary drawbacks of manual inspection is its subjectivity. Different inspectors may perceive fruit quality differently based on their judgment and experience. This subjectivity can lead to inconsistencies in assessment outcomes, where the same fruit may be judged differently by different inspectors. Such discrepancies undermine the reliability and consistency of the inspection process [17], impacting the overall quality control efforts.

Furthermore, manual inspection is labor-intensive, requiring a significant amount of manpower, especially for large-scale fruit production and processing operations. Trained personnel need to carefully examine each fruit, which not only increases operational costs but also extends processing times. The need for manual labor also introduces the potential for human error, as inspectors may overlook defects or inaccurately assess fruit quality under time constraints or fatigue. Moreover, traditional methods of fruit inspection lack scalability, particularly in the face of expanding global supply chains and increasing consumer demands. With the globalization of trade and the rise of e-commerce, the volume of fruits moving through supply chains has grown exponentially. Manual inspection methods struggle to keep pace with this growth, leading to bottlenecks in the production and distribution process.

In summary, while traditional methods of fruit inspection have been a mainstay in the industry for years, they suffer from inherent limitations. These methods are subjective, labor-intensive, and lack scalability, posing challenges for ensuring consistent and efficient fruit quality assessment and defect detection. As such, there is a pressing need for innovative solutions that can overcome these challenges and modernize fruit inspection practices in the agricultural industry.

3.3 Advancements in Deep Learning

Recently, the field of artificial intelligence, and especially deep learning, has appeared as a changing factor that helps in the revolution of the traditional fruit-checking method. On the other hand, deep learning models have become one of the central themes arising, which holds the greatest researcher interest at present because of Convolutional Neural Networks applied to different image-related tasks, from recognition and classification to object detection. More importantly, learning in deep schemes is directed at the automatic extraction of features [18] and complex patterns from raw data without manual engineering. This is particularly exploited in the context of fruit inspection, where the visual appearance of the fruit contains rich information that characterizes its quality and its potential defects. Very large datasets, wherein the data is raw but labeled, are used to train the deep learning models, which will teach the automated process of recognizing and classifying them as well as detecting and localizing the different types of defects.

From an anatomical point of view, the animal visual cortex provides the main principles in organizing an important class of effective models in image analysis: Convolutional Neural Networks. CNNs are a type of deep learning model that has been very successful in various types of image-related tasks. The basic building blocks of CNN are multiple layers of convolutional and pooling, followed by fully connected classification/regression. From the perspective of the supervised learning [19] process, raw pixel values serve as inputs to CNN to derive an automatic learning strategy for the hierarchy presented in the feature representation.

The ability of a deep model, like CNN, to learn and classify fruits comes from the ability to derive intricate patterns and features from a huge dataset. Such huge image data can be effectively processed by these deep learning models in real time or quasi-real time so that accurate prediction or classification may be achieved, with appropriately designed and powerful computational resources, particularly with GPU and distributed computing systems. Moreover, with deep learning, there is the flexibility of models to be adapted for various tasks of fruit inspection, among which quality assessment and defect detection stand out. For example, a CNN model trained for the grading of different quality grades of fruits by assuming that they have some visual appearances like ripeness, size, and color. Bruises, blemishes, or rotting on fruit surfaces may also be similarly located by such models.

Lastly, advances and popularization of deep learning, especially Convolutional Neural Networks, have brought radical improvements to fruit inspection. The other advantage of deep learning is that their models are allowed to learn the complex patterns and features directly from large datasets and powerful computations made to achieve accurate predictions/chunked information regarding the good execution of fruit quality assessment and defect detection. It is very promising for deep learning [20] to innovate and enhance fruit inspection practices in modernized agriculture.

3.4 Importance of Deep Learning in Agriculture

Deep learning applied in agriculture is a turning point and has far-reaching technological implications for various aspects of the value chain in crop management, optimization of yield, and quality control. Deep learning has the upper ground compared to traditional techniques in assessing fruit quality and detecting defects, hence reasserting its superiority in the present agricultural practice. First, deep learning automates the process, which has been a paradigm shift because manual processes require a lot of labor for very efficient operations. When powerful algorithms and computational resources are deployed, deep learning models will automatically process a lot of data, which, in turn, reduces reliance on human effort and ensures that the process of decision-making is highly accelerated.

Reduced labor but high throughput and greatly enhanced operation efficiency can be effected through automation of the examination of fruit quality and defect detection throughout the agricultural value chain. More so, deep learning enhances accuracy, as it leverages machine learning [21] in extracting more complex patterns and features from significant datasets. The very fact that such models are trained on enormous, varied datasets containing annotated examples enables the capability of deep learning models to pick the lightest nuance up and make objective judgments with a high degree of precision. The way this learning system can create complex representations from data leads to more consistent and reliable assessments of fruit quality and defects, and that leads further to assured improvements made in total product quality and customer satisfaction.

What is more, deep learning allows scalable technology in the sense that the solution, apart from being given at a universal level, can also be given in many different environments and productions. Deep learning systems are flexible and scalable according to the needs of a small family farm or a large commercial plantation, with unmatched operational needs and environmental conditions for traditional inspection methods. This scalability is what allows the wide adoption of deep learning technologies in the agricultural sector, hence empowering the growers and producers to achieve greater efficiency and scale economies.

In short, the application of deep learning in agriculture, especially in the assessment of fruit quality and defect detection, has not had much research done. These deep learning technologies indicate that upcoming agribusiness practices in automation, accuracy, and scaling exist in a new dimension toward efficiency, productivity, and sustainability. With agriculture facing and embracing new opportunities and challenges, deep learning is arising as an innovation and transformational factor throughout the whole value chain.

3.5 Challenges and Opportunities

Deep learning has the potential to revolutionize quality inspection of fruits and defect detection with automation, better precision, and scalability in most agricultural settings. Therein lies an interesting set of challenges relevant to engaging opportunities. Although deep learning has the capability of revolutionizing quality inspection [22] of fruits and defect detection with automation, better precision, and scalability, the practice of doing the process has some barriers: how to make such models generalize to unseen data and other varieties of fruits, how to make the process not laborious, time-consuming, logistic in all ways, and ethical in concern regarding data privacy, consent, and the mitigation of bias.

Challenges:

1. Data Annotation:

Labor-Intensive Process: Generally, the protocols designed for large-scale data annotation necessitate significant human efforts on the part of annotators [23], who may need to undertake the tedious task of labeling thousands or millions of fruit images.

Annotation Consistency: This means that the labeling should be all the time consistent between annotators to avoid conflicts and biases in the training dataset. In most cases, this would entail strict quality control. Annotations The Complexity of various quality attributes and defects in many categories, such as maturity levels, size deviations, and multiple defect types, makes the process complex.

2. Model Generalization:

Domain adaptation: Deep learning models, if trained on one dataset, might not generalize well on the other data or different varieties of fruit [24] because of the domain shift; hence, techniques like domain adaptation or transfer learning might come in handy.

Enable strategies for class imbalance: Since it has imbalances in the samples, it also means an imbalance of the distribution of quality attributes and defect categories in training sets, leading to biases and poor generalization performance.

Robustness to environmental variability: Deep learning models must be invariants toward environmental variability, such as those of light, changes in the background, clutter, and occlusions, among others, to guarantee proper performance in real-world conditions.

3. Real-world Deployment:

Hardware Constraints: Implementation of deep-learning systems into the resource-constrained agriculture domain faces some stringent challenges due to less availability of mere computational resources, which hence require optimization of model architectures and inference algorithms [25]. The deep learning system should consider compatibility and interoperability upon integration with an already existing agricultural infrastructure, either through farm management software or IoT devices.

Acquisition and Connectivity: Data transfer from these remote locations to center-based deep learning systems is likely to be lost due to connectivity issues and bandwidth limitations, which means that data collection and sending will be impossible. This then calls for offline or edge-computing solutions.

4. Ethical Considerations:

Observation of data privacy and consent when data owners are human: This also includes situating current data protection regulations and ethical guidelines for the data. Bias mitigation: Ensure training data are free from bias with demographic information or sampling information, which can lead to discriminatory outcomes and further deny fairness and equity in model prediction.

Model transparency and accountability: There is currently a rising call for open deep learning models and ways in which accountability [26] and recourse can be built in the case of any erroneous or unintended adverse effect on stakeholders. Consequences are critical for building trust and acceptance among stakeholders.

Opportunities:

1. Innovation in Deep Learning Techniques:

Architectural innovations: New architectures, like attention mechanisms, and graph neural networks, especially for fruit quality assessment to detect defects of better quality, leading to more effective and efficient models.

Optimization algorithms: the special design of optimization algorithms regarding the requirements of meta-learning or Bayesian optimization for proper fine-tuning deep learning models to agricultural data; facilitating an increase in speed of convergence and generalization performance.

Training strategies: New training strategies include, but are not limited to, curriculum and self-supervised learning to increase the resilience and adaptability of deep learning models under varying production scales of agricultural environments.

2. Scalable and Efficient Solutions:

Edge Computing Solutions: Development of lightweight and energy-efficient deep learning models that can be deployed on edge devices, like drones or field sensors, to empower real-time processing and analysis of agricultural data at the point of collection.

Cloud-Based Solutions: The power of cloud computing will help scale model training and inference, as well as on-request processing of large-scale agricultural datasets, fostering collaboration and knowledge sharing between researchers.

Distributed Learning Frameworks: More precisely, it uses distributed learning frameworks through federated and ensemble learning frameworks that ensure the privacy and security of data while collaboratively training deep learning models across several agricultural sites.

3. Interdisciplinary Collaboration:

Domain Expertise Integration: Teaming deep learning models with domain knowledge, in collaboration with domain experts in agriculture [27] such as agronomists, horticulturists, and food scientists, make the results contextually meaningful and explainable. So, models can claim legitimacy in accuracy when applied within the agricultural domain.

Cross-disciplinary Research: Working with other computer vision, machine learning researchers, robotic engineers, and agricultural engineers promotes even greater ease of interchange of ideas and methodologies in the research. Cross-fertilization of expertise in devising innovative, efficient solutions for fruit quality assessment and defect detection will boost innovative development in such a way that it results in very advanced and reliable models.

4. Real-world Impact:

Socio-economic benefits: Proper exploitation of deep learning potentials in agriculture would be realized in the augmentation of agricultural productivity, reduction of post-harvest losses, and the uplift of livelihood levels of the farmer and other dwellers in rural settings. This improvement in quality and defect detection of fruit aids in the effective and efficient utilization of resources, and less use of pesticides [28] thus avoiding their wastage, among a lot of other broad aims of sustainability and environmental stewardship.

It does, however, remain an effort of the researchers, practitioners, policymakers, and other stakeholders within the system themselves if the challenges and opportunities that will come with the adoption of deep learning within the agricultural systems have to be ably dealt with. In dealing with these challenges, deep learning [29] does have the potential to revolutionize the assessment of fruit quality and defect detection, impacting the sustainability, resilience, and equity of agricultural systems.

CHAPTER 4

PROPOSED METHODOLOGY

4.1 PROPOSED SYSTEM

The system depicted in Figure 4.1 utilizes a hybrid approach that combines segmentation and object detection technologies [30] to accurately identify and demarcate safe driving zones. This methodology takes advantage of the enhanced precision provided by these techniques, ensuring reliable delineation of navigable areas.

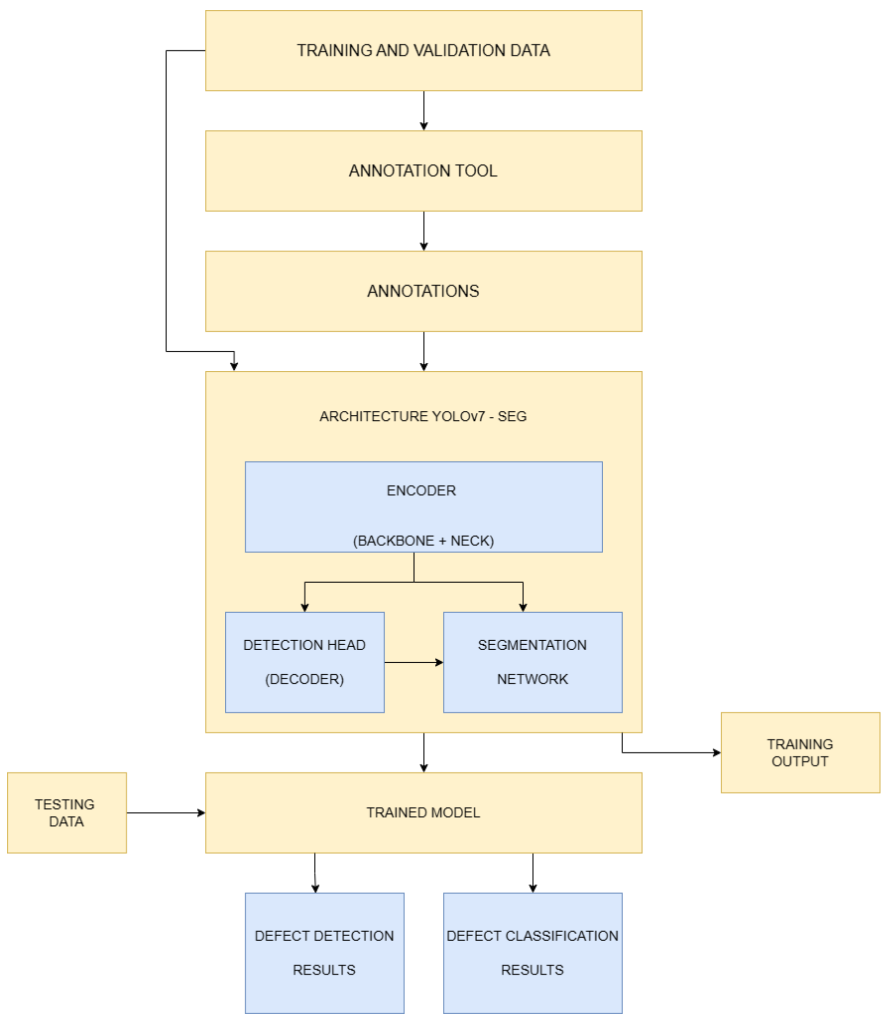

Figure 4.1 Proposed System

So, since the methodology is based on both segmentation and object detection, it intends to improve the accuracy and reliability of the detection of the drivable area. First, the road-scene images are annotated manually. The vehicles are drawn with bounding boxes, while the classes that are segmentation-oriented [31] are annotated with polygon-based annotations. Before the training process, the road images undergo an annotation process in which each image receives a detailed annotation, and its annotations are written to a text file (txt). The numeric values written in the text file indicate floating-point numbers lying between 0 and 1, which describe the whole properties of the road scene in brief. Then, these annotated images are poured over into the training module where the YOLOv7 model acts robustly as a central entity. So, three segmentation labels have been used: that is, the drivable region, the lane lines, and the pothole; while two object detection labels have been used—the cars and trucks. In this approach, instance segmentation has been proposed, inspired by YOLOv5 and YOLOv6; based on them, some works have been done and developed an anchor-free instance segmentation approach. Finally, the testing data have been fed into the trained model [32] to get the detection and segmentation results from their heads, respectively.

4.2 YOLOV7 ARCHITECTURE

YOLOv7 is an encoder-decoder configuration, and the design has been kept very complex. It has two parts: the first part is the backbone, and the second part is the neck network. Backbone This is a feature extraction network capable of generating feature maps of different resolutions. The feature map starts with a size that is one-sixteenth the original size, denoted by P1, gradually increasing up to a size that is one-thirty-second of the original size, denoted by P5, and occupies the resolution scope in the overall spectrum.

This is a very complex process that the network performs and takes about 50 layers to perform it. To elaborate further on the feature-learning capabilities of the backbone, a host of advanced methodologies and components have been introduced in the backbone, and these are placed strategically. The following list is the set of modules constituting the backbone. E-ELAN, which stands for Extended Efficient Layer Aggregation Network, improves the ability of the backbone in feature learning by exploiting the cardinality of the "Expand, Shuffle, and Merge" and group convolutional methodologies, and this results in a much better diversity in aspects learning, and the gradient pathway remains intact with no compromise. This is done using the Max-Pooling (MP) layer. Next, the module concatenates the input tensor with the pooled outputs, and multi-scale region aspects are obtained by such a pooling and concatenation operation. Convolution Batch Normalization layer—In deep learning, a convolution and batch normalization layer are merged into a single convolutional layer. This is a very popular technique, as the advantages have been proved and include ameliorated efficiency and deductions in computational cost. Adding the batch normalization step to the convolution in this way promotes the model to learn more informative data representations while also providing input normalization for each layer in unison.

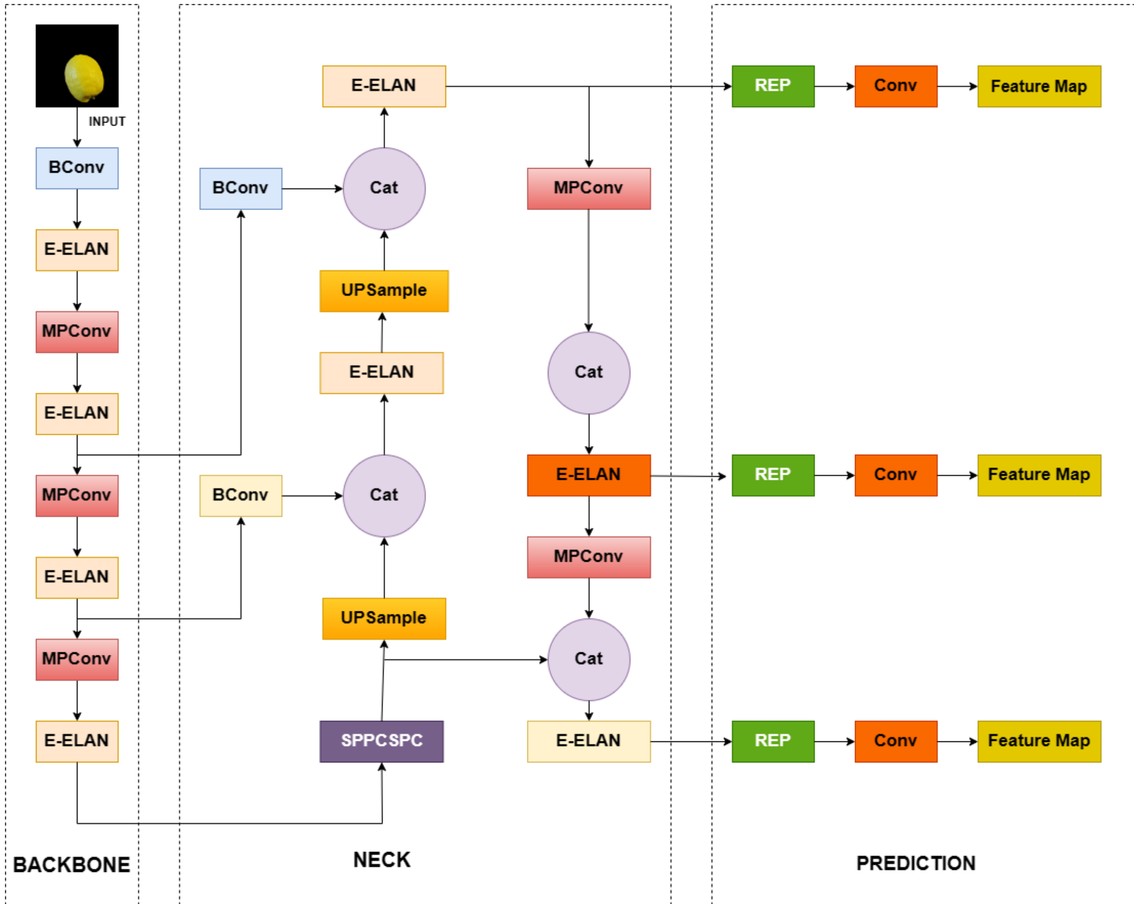

Figure 4.2 YOLOv7 detailed Architecture

In this model, YOLOv7 is deep-scaled into fusion with multiple other alternative models of various scales with a diverse inference speed. This can be achieved by adapting its scale factors and stage adaptation to develop separate-sized prepared models. Depth and width factors are scaled to afford models to achieve peak performance without changing the properties of the representation. In YOLOv7, the RepConv technique, designed with a module-level ensemble, is readied for trainable BoF implementation using the RepConv technique. It uses a mix of 3x3 and 1x1 convolutions with an identity connection; however, in YOLOv7, RepConvN retains the residuals and concatenation but does not use the identity connection. Re-parameterization is further done within CBN for better results.

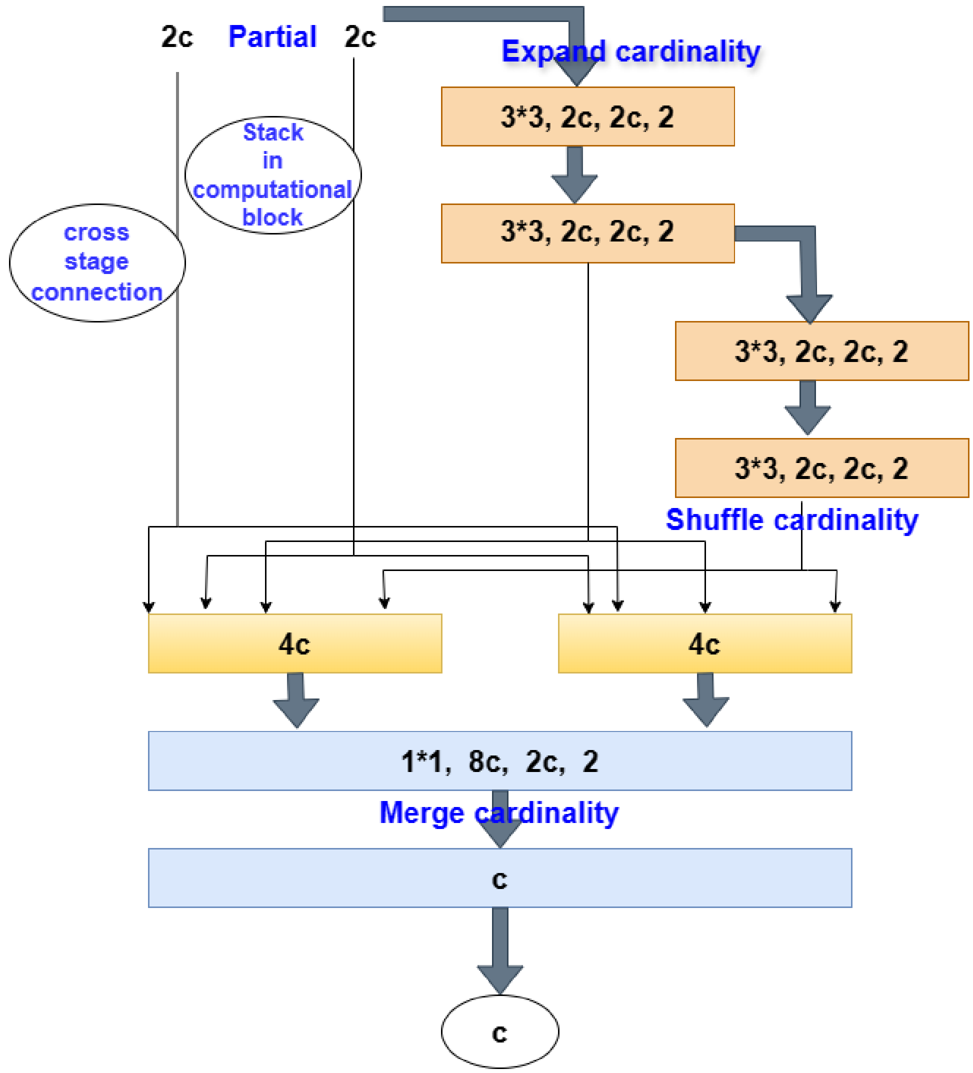

Figure 4.3 E-ELAN Module

SPP (Spatial Pyramid Pooling) module: It is one of the crucial designs within the architecture of the network, which forwards pooling with different kernel sizes without loss of resolution of the input (stride == 1). The said usage is made for the maximal pooling layers. Thereafter, it concatenates the original input tensor with the pooled outputs. This yields multiscale region features since it utilizes pooling and concatenation operations. In contrast, the CSPNet has been designed to attack the problem of redundant gradient growth. It divides the feature map of the base layer into two parts, where one is used for the operation of blocks (like a dense block or a reblock) and then a transition layer, and the other part is then merged with the transmitted feature map for the following stage's usage. In this way, the high computation complexity, memory consumption, and duplication of gradient information can be well reduced, and the inference speed and accuracy of the network are effectively enhanced.

The YOLOv7 model introduces a two-headed novel way to boost its capability toward segmenting the object and accurately locating it on the image. The front head is designed for the final output, while the assistant head is to help in training with shallow and superficial weights along with the assistant loss in guiding. Deep supervision is integrated when adding a label assigner. In this framework, a label assigner can produce soft and coarse labels in the optimizing learning process. It makes the head capture residual information.

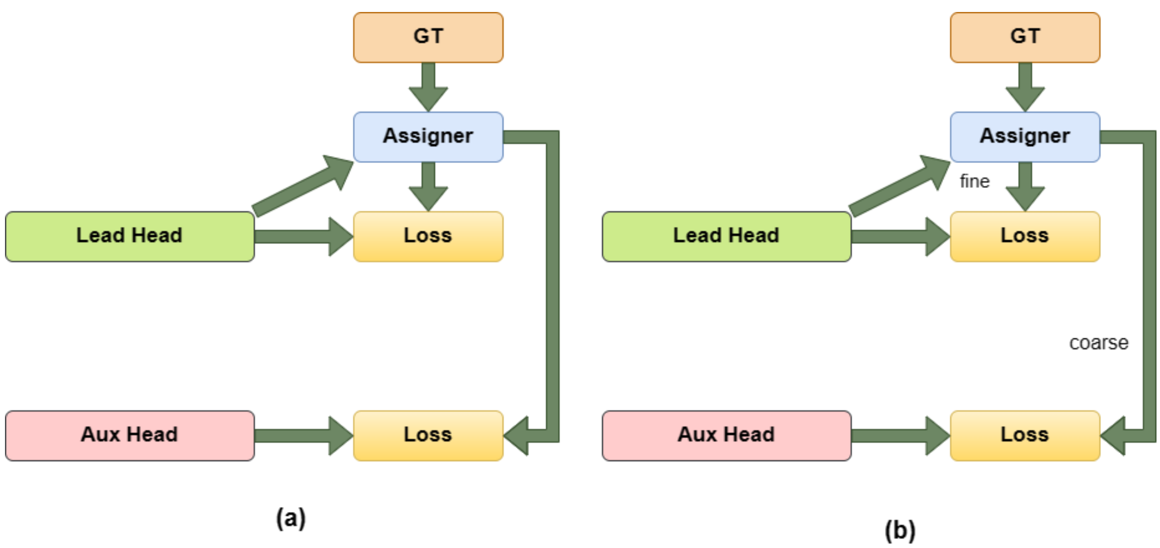

Figure 4.4 Label Assignment in YOLOv7

4.3 SEGMENTATION

YOLOv7 architecture introduces an instance segmentation technique to build more innovatively over the YOLOv5 and YOLOv6 designs, shedding the anchor mechanics and using the mechanic of the anchor-free type. Basic to the instance segmentation performance by YOLOv7 is the design with components akin to what ProtoNet—a compact, fully connected neural network—used. Grandly, the ProtoNet integration within the object detection head of YOLOv7 model architecture marries the founding philosophy of the ProtoNet with the strong technologies of object detection. This architecture of the YOLOv7 ensures, in an unparalleled way, that prototype masks are generated. Further, these prototype masks are indeed an important element for the proper operation of the instance segmentation model. In this way, the method gains resemblance with that of the Fully Convolutional Networks, or FCNs, which are already widely leveraged in use for a host of problems in the domain of semantic segmentation. Thereby, YOLOv7 remains lightweight and accurate enough for segmenting or breaking down the targeted objects in images. The use of YOLOv7 is advantageous based on this dual property: prototype masks are generated, and from this, accurate segmentation is ensured. This is the innovative confluence of the principles of the ProtoNet network with the advanced object detection frameworks.

4.4 LOSS FUNCTION

The global loss function aggregates the loss of a few components to provide an analysis of aspects that relate to the network's task. One of the measures of mismatch that occurs between the ground truth and the predicted segmentation mask is segmentation loss. Similarly, the bounding box loss measures the mismatch that occurs between the observed and predicted bounding boxes. Detection loss measures the mismatch that exists between the predicted outcome and an actual object on the ground having been detected. In contrast, the classification loss measures the mismatch that exists between the actual class labels and the predicted class. A well-trained network can optimize itself for multiple aspects of the given task effectively using these different loss components.

$$loss = Segment.loss + Bounding\ Box\ loss + Detection\ loss + Class.loss \qquad (4.1)$$

A loss function forms one of the key building blocks in evaluating how good a model is concerning input data. It gives a difference between values that are predicted by the model and the actual target value given in the data.

Key highlights are:

The loss function guides how the neural network is to be trained by giving a measure of error that needs to be minimized over the training. It gives the error gradient, and after finding that, it updates the weights to minimize this error by optimization algorithms, like gradient descent.

Common types of loss functions include

Mean Squared Error (MSE): Generally used on regression, it simply means squaring the difference between the predicted value and that of the actual value and then getting the average. It is sensitive to outliers because it squares errors.

Cross-Entropy: This is quite popularly used in classification tasks. For binary classification, it is called binary cross-entropy, and for multi-class problems, it is referred to as categorical cross-entropy. This quantifies the difference between two probability distributions-in this case, the cross-entropy finds the number of bits required to encode the ideal coding scheme, according to one distribution when the wrong coding scheme is being used to code according to another distribution.

Mean Absolute Error (MAE): This is useful for regression: on regression, this measures the average magnitude of errors in a set of predictions, without considering direction-that is, it aggregates errors by finding their average over the absolute values of the errors.

Hinge Loss: Generally used in binary classification problems like those encountered in working on the Support Vector Machine algorithms, this loss function is suitable for use with binary classification where the target values are in the set $\{-1,1\}$. Notice that as given, this loss function increases the margin when the sample is classified correctly; it will only make updates to the margin when the sample is classified incorrectly.

Huber Loss: Huber Loss is a combination of MSE and MAE but is less sensitive to outliers than MSE. Currently, it performs like MSE for small errors and MAE for large error

CHAPTER 5

EXPERIMENTAL RESULTS

5.1 DATASET PREPARATION

It was initiated by a dataset, consisting of 2,690 different fruit images in their various types, varieties, sizes, colors, and environments, properly prepared. High emphasis was put on correctly labeling each image by the type of fruit; hence, forming a very strong base for the supervised learning framework. All the images have been resized to a common 224 × 224 dimensions, and the pixels were normalized in the range of 0 to 1 for consistent and fast use within the neural networks. To further increase categorical classification, the numerical value was encoded against fruit labels. All these have been fed through a new dataset, using most of the recommended and common augmentation techniques for making a total of 6456 images counted in the below table.

Table 1: Dataset Summary

Class	No. of Images	Training	Validation	Test
Healthy	2000	1760	160	80
Blemish	1500	1320	120	60
Pedicel	1200	1056	96	48
Gangrene	1000	880	80	40
Mould	756	633	62	31
Total	**6456**	**5649**	**538**	**269**

The set of augmentation techniques includes shearing, rotations, flips, scaling, translations, and brightness specifications. Given pixels are fundamentally shifted along the prescribed axis, shearing augmentation allows the images to be subjected to a controlled level of basic distortion. Flipping essentially means changing the orientation of an object; therefore, for a flip, the left and right are changed to their opposite from the original. Therefore, rotation and flipping will thereby train the model to recognize fruits in different orientations and their mirror images in those orientations. Flipping, like rotation, has to do with the change in orientation that the object is brought into view. Essentially, scaling helps to train the model with data in the training set to recognize that sometimes images change size, though it is of the same thing, and sometimes it is a different "distance" away from the camera. In translation, it trains the model to recognize pictures as they are "moved" across the different parts of the frame. Finally, adjusting brightness would train the model to recognize the same fruit but in various lighting. This augmentation is necessary to make the dataset rich in diversity and represent the various variations over which the model should generalize for real-world cases of unseen data.

Thereafter, over 70:20:10%, the data set was stratified into training, validation, and evaluation sets. This further vouched for the fact that each set maintained proper distributions across all fruit classes, hence the integrity and diversity of this dataset at every stage of model development. Quite large training sets were there to fit models, yet the significant role of the validation set in hyperparameters and prevention from overfitting cannot be ignored. The test set provides an unbiased assessment of the final model. This dataset was prepared and augmented carefully to provide a strong base for the YOLOv7 model to be trained. This file tunes the VGG16 model using linear network topology search for lemon quality classification over 2690 images.

5.2 PERFORMANCE METRICS

A diverse range of performance metrics has been employed to assess the effectiveness of the model. One key metric is Intersection over Union (IoU), which quantifies the extent of overlap between segmented areas by calculating the ratio of their common intersection to their union. This metric is crucial for evaluating the segmentation aspect of the model.

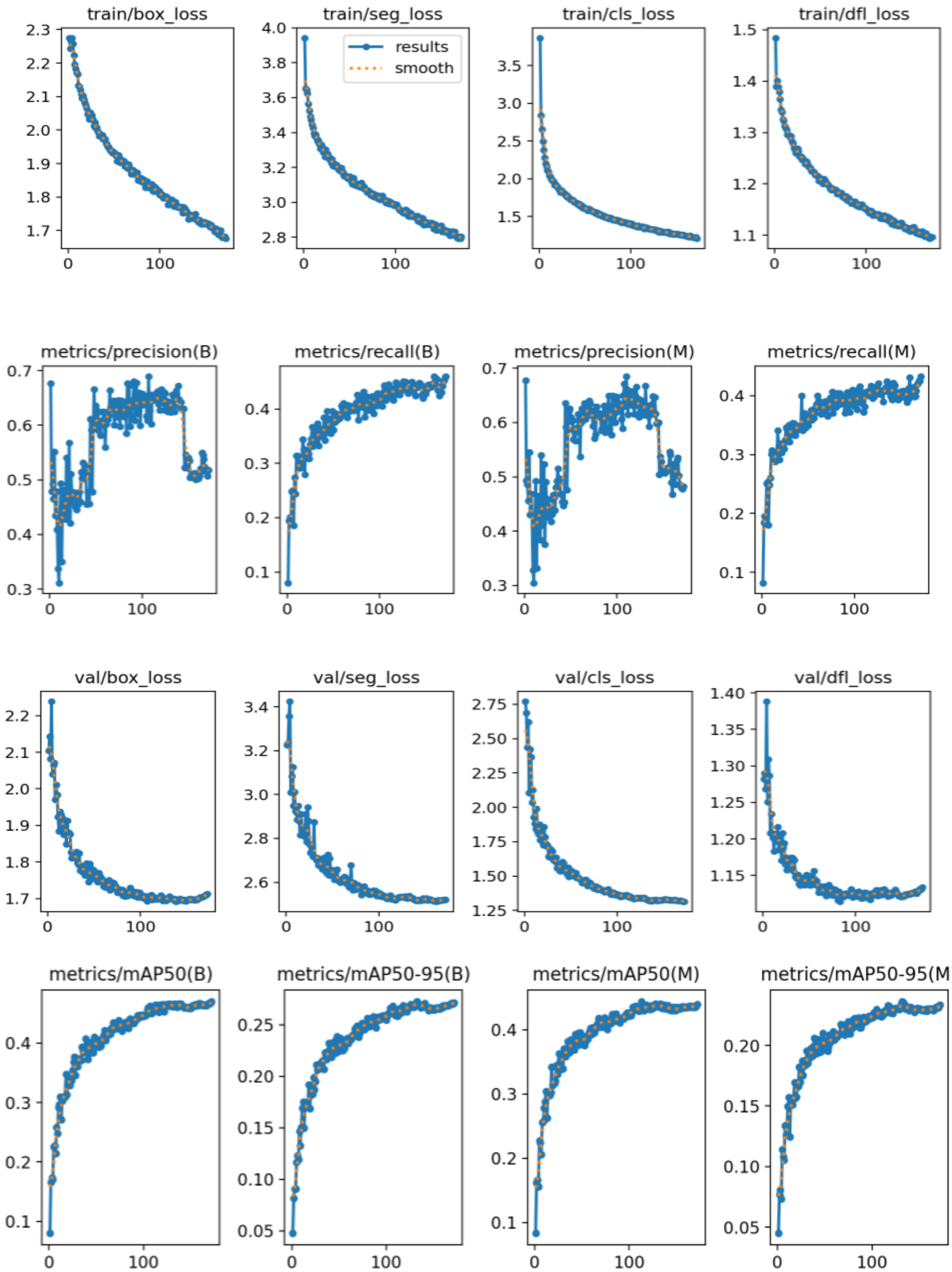

Figure 5.1 Performance metrics plots

detection component, several evaluation measures are adopted: precision, recall, F1-score, and mean Average Precision (mAP). Precision measures the proportion of correctly identified positive detections out of all detections made, indicating the accuracy of the positive predictions. Recall, on the other hand, represents the proportion of actual positive instances correctly identified by the model, reflecting its ability to capture all relevant instances.

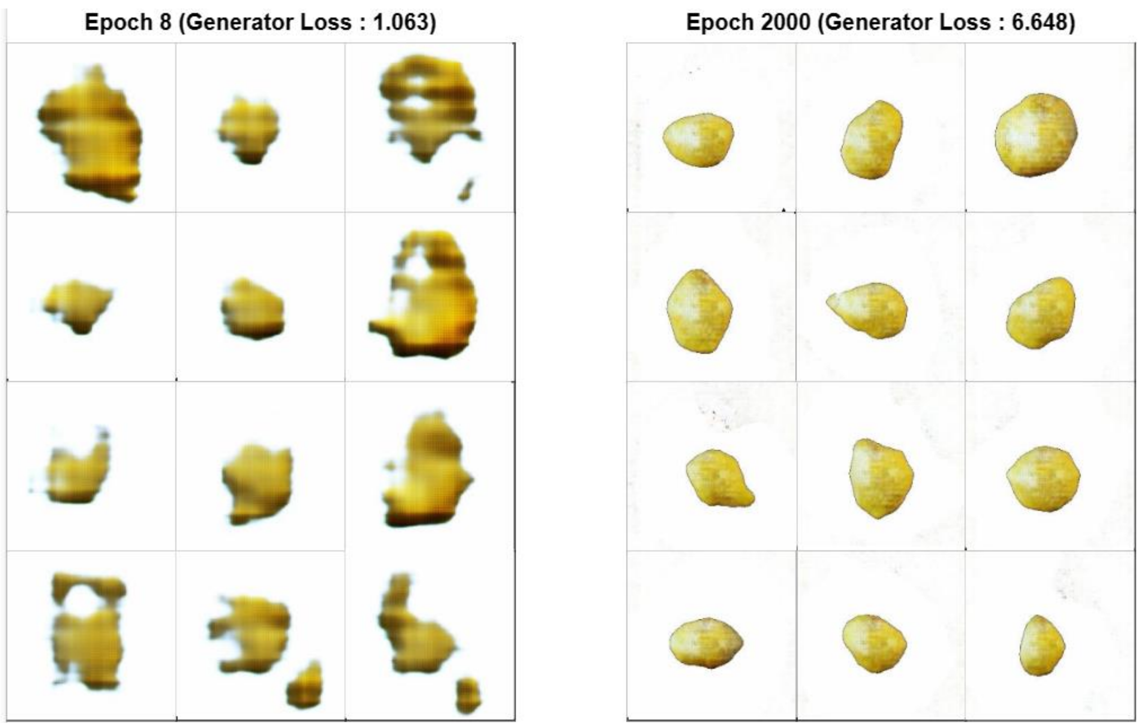

Figure 5.2 Generator outputs at the lowest observed loss compared to the final epoch

The F1-score is a combined metric that balances both precision and recall, providing a single measure that accounts for both false positives and false negatives. It is particularly useful when there is an uneven class distribution. Lastly, mAP (mean Average Precision) calculates the average precision across different object categories, offering an overall assessment of the detection performance. mAP is especially valuable for multi-class detection problems as it considers the precision-recall curve for each class and averages them to provide a comprehensive performance evaluation. These metrics together provide a thorough evaluation of both the segmentation and detection capabilities of the model, ensuring its robustness and reliability in various real-world applications.

$$\boldsymbol{Recall(R)} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \qquad (\mathbf{5.1})$$

$$\boldsymbol{Precision(P)} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \qquad (\mathbf{5.2})$$

$$\boldsymbol{F1_{score}} = \frac{\boldsymbol{2RP}}{\boldsymbol{R+P}} \qquad (\mathbf{5.3})$$

5.3 SYSTEM REQUIREMENTS

For implementing the proposed methodology, the following setup was used: Ubuntu Linux 22.04.01 running on an NVIDIA RTX A5000 GPU for training, validating, and testing the model. To train the model with supported strong GPUs like those in the series of NVIDIA Tesla, Google Colab was used in coordination with Google Drive for data management. I implemented it in Google Colab to get better computational resources; otherwise, the following are the details for the environment setup: I have an 11th Gen Intel Core i5-1135G7 processor with 16 GB of RAM and Windows 11 Home Single Language Version 23H2.

5.4 RESULTS AND DISCUSSION

Results and Discussion Data Pre-processing and Model Training This study adapted a dataset containing 2,690 lemons images obtained from the dataset by SoftwareMill. The healthy or unhealthy status of the fruit was afterward labeled with two binary labels each. Picking 2,400 of these images to create our training set, while taking 290 images for validation. We implemented a training procedure for all combinations of the number of epochs and batch sizes for each configuration. The training approach was modified in such a way that it gave the best result for a batch size of 16 run over 50 epochs using our Convolutional Neural Network (CNN) and YOLOv7-based model.

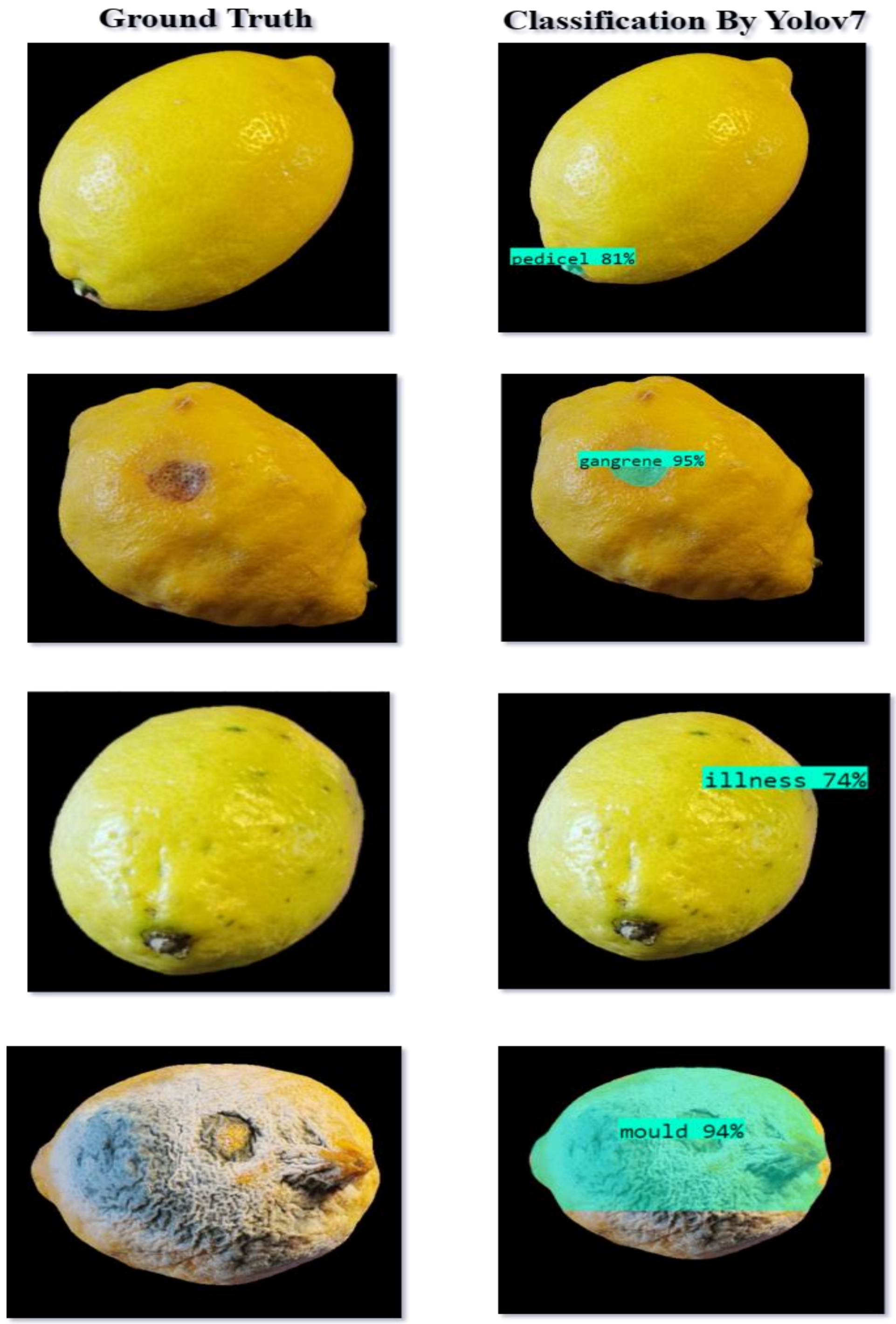

Figure 5.3 Model Results. (a) Ground Truth, (b) YOLOv7 Classifications. The YOLOv7 model demonstrates superior performance in detecting and classifying various fruit defects such as blemish, pedicel, gangrene, and mould

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

We present a deep learning-based approach for the classification of fruit quality and defects using CNN and YOLOv7. Our developed model has achieved an accuracy of 79.6%, which is slightly lower compared to the 83.77% of the base research paper. However, our approach significantly improved the computational efficiency of deep learning models by reducing the training and evaluation time to about 10.6 hours on standard computational systems compared to 18 hours taken by existing models using high-performance GPU systems.

Key Contributions and Findings

Model efficiency: The derived model shows great improvement in the spent computational time. This greatly reduced the training time without using high-end GPUs based on the optimization of network architecture and the use of YOLOv7. Therefore, this would make the approach more practicable in various environments, more so where advanced hardware might not be available.

Balancing Performance: Our model balances accuracy with computational demand, where the accuracy obtained lies just below the benchmark, hence used to give this model an edge—that this type of model is feasible for practical deployment into the real world.

For Real-Time Robust Architecture: We have been able to make the design for a more robust real-time application architecture. Feature diversity is enhanced when it is combined with matchless learning capacity through feature extraction and detection by advanced methods using YOLOv7. The network in the network: This makes the model use the E-ELAN which increases feature diversity and the learning capacity.

Future Scope

The following are a few future research and development opportunities in the enhancement and scalability of this approach: Data scarcity can be reduced by integrating CGANs in the training process to generate synthetic data. This will enhance the training examples to be diverse and realistic, resulting in better generalization into real-world applications. This model can be optimized for deployment on the edge and mobile platforms to make in-field fruit quality assessment possible in real-time.

This involves the reduction of the computation requirement of the model and making it work efficiently over less powerful hardware. This model could be seamlessly integrated with automatic sorting and packaging systems to increase operational efficiency in processing plants, which will enable them to detect and classify fruit defects in real-time. Reducing the number of sorting processes by classifying a more varied range of fruits and more than one type of defect is possible by expanding the dataset and retraining the model. Multi-sensory approach in the analysis of fruit quality by building features from the visual sensory data and combining it with other sensory data like hyperspectral imaging and electronic noses Better levels of accuracy could be obtained by continuous exploration in hyperparameter tuning, architecture refinement, and techniques like neural architecture search.

Development of model capability by the implementation of advanced training techniques like self-supervised learning, transfer learning, and fine-tuning on task-specific data The use of auto-pruning techniques to reduce the model size and to increase the speed of inference for running on resource-constrained devices Model debugging and trust has to be built by increasing the explainability of models using techniques such as Grad-CAM. Large-scale deployment and real-world trials will bring the capability of generalization and scaling up proof of the model, while continuous learning mechanisms will ensure the model updates with changes in conditions and new data. Conclusively, this research would suggest that deep learning-based fruit quality and defect classification could be made efficient and effective. The model they proposed achieved competitive accuracy with much-reduced computational requirements, which made it more feasible for real-world applications. The model can still be further fine-tuned with the majority of the outlined future works to have higher accuracy, efficiency, and field applications in the agricultural industry.

REFERENCES

[1]. Aherwadi N, Mittal U. Fruit quality identification using image processing, machine learning, and deep learning: A review. *Adv Appl Math Sci*. 2022;21(5):2645-2660.

[2]. Jana S, Parekh R, Sarkar B. Detection of Rotten Fruits and Vegetables Using Deep Learning. In: Uddin MS, Bansal JC, eds. *Computer Vision and Machine Learning in Agriculture*. Algorithms for Intelligent Systems. Springer Singapore; 2021:31-49. doi:10.1007/978-981-33-6424-0_3

[3]. Bhole V, Kumar A. Mango Quality Grading using Deep Learning Technique: Perspectives from Agriculture and Food Industry. In: *Proceedings of the 21st Annual Conference on Information Technology Education*. ACM; 2020:180-186. doi:10.1145/3368308.3415370

[4]. De Luna RG, Dadios EP, Bandala AA, Vicerra RRP. Tomato fruit image dataset for deep transfer learning-based defect detection. In: *2019 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM)*. IEEE; 2019:356-361. Accessed May 23, 2024. https://ieeexplore.ieee.org/abstract/document/9095778/

[5]. Da Costa AZ, Figueroa HE, Fracarolli JA. Computer vision based detection of external defects on tomatoes using deep learning. *Biosystems Engineering*. 2020;190:131-144.

[6]. Palakodati SSS, Chirra VRR, Yakobu D, Bulla S. Fresh and Rotten Fruits Classification Using CNN and Transfer Learning. *Rev d'Intelligence Artif*. 2020;34(5):617-622.

[7]. Aguiar HT, Vasconcelos RCS. Identification of External Defects on Fruits Using Deep Learning. In: Pinho AJ, Georgieva P, Teixeira LF, Sánchez JA, eds. *Pattern Recognition and Image Analysis*. Vol 13256. Lecture Notes in Computer Science. Springer International Publishing; 2022:565-575. doi:10.1007/978-3-031-04881-4_45

[8]. Raja SP. Fruit quality prediction using deep learning strategies for agriculture. *International Journal of Intelligent Systems and Applications in Engineering*. 2023;11(2s):301-310.

[9]. Mirra KB, Rajakumari R. Classification of Fruits using Deep Learning Algorithms. Published online 2022. Accessed May 23, 2024. https://scholar.archive.org/work/zgegbry5wrf5jc542pxndeb7pq/access/wayback/https://assets.researchsquare.com/files/rs-1495878/v1/f7783cb9-91c1-415f-9fc6-8f663144c756.pdf?c=1648825707

[10]. Dhiman B, Kumar Y, Kumar M. Fruit quality evaluation using machine learning techniques: review, motivation and future perspectives. *Multimed Tools Appl*. 2022;81(12):16255-16277. doi:10.1007/s11042-022-12652-2

[11]. Ghazal S, Qureshi WS, Khan US, Iqbal J, Rashid N, Tiwana MI. Analysis of visual features and classifiers for Fruit classification problem. *Computers and Electronics in Agriculture*. 2021;187:106267.

[12]. Srinivas R, Yadiah B. Deep learning based fruit quality inspection. *Int J Res Appl Sci Eng Technol*. 2022;10:4535-4539.

[13]. Knott M, Perez-Cruz F, Defraeye T. Facilitated machine learning for image-based fruit quality assessment. *Journal of Food Engineering*. 2023;345:111401.

[14]. Gill HS, Murugesan G, Mehbodniya A, Sajja GS, Gupta G, Bhatt A. Fruit type classification using deep learning and feature fusion. *Computers and Electronics in Agriculture*. 2023;211:107990.

[15]. Sudhakara M, Ghamya K, Karthik SA, Yamini G, Mahalakshmi V. A Statistical Analysis of Fruit and Vegetables Quality Detection and Disease Classification for Smart Farming. *Journal of Algebraic Statistics*. 2022;13(2):1426-1438.

[16]. Mehta D, Choudhury T, Sehgal S, Sarkar T. Fruit Quality Analysis using modern Computer Vision Methodologies. In: *2021 IEEE Madras Section Conference (MASCON)*. IEEE; 2021:1-6. Accessed May 23, 2024. https://ieeexplore.ieee.org/abstract/document/9563427/

[17]. Soltani Firouz M, Sardari H. Defect Detection in Fruit and Vegetables by Using Machine Vision Systems and Image Processing. *Food Eng Rev*. 2022;14(3):353-379. doi:10.1007/s12393-022-09307-1

[18]. Singh S, Singh NP. Machine Learning-Based Classification of Good and Rotten Apple. In: Khare A, Tiwary US, Sethi IK, Singh N, eds. *Recent Trends in Communication, Computing, and Electronics*. Vol 524. Lecture Notes in Electrical Engineering. Springer Singapore; 2019:377-386. doi:10.1007/978-981-13-2685-1_36

[19]. Ashtiani SHM, Javanmardi S, Jahanbanifard M, Martynenko A, Verbeek FJ. Detection of mulberry ripeness stages using deep learning models. *IEEE Access*. 2021;9:100380-100394.

[20]. Mohapatra D, Das N, Mohanty KK, Shresth J. Automated Visual Inspecting System for Fruit Quality Estimation Using Deep Learning. In: Mishra M, Sharma R, Kumar Rathore A, Nayak J, Naik B, eds. *Innovation in Electrical Power Engineering,*

Communication, and Computing Technology. Vol 814. Lecture Notes in Electrical Engineering. Springer Singapore; 2022:379-389. doi:10.1007/978-981-16-7076-3_33

[21]. Khatun M, Ali F, Turzo NA, Nine J, Sarker P. Fruits classification using convolutional neural network. *GRD Journals-Global Research and Development Journal for Engineering*. 2020;5(8):1-6.

[22]. Safari Y, Nakatumba-Nabende J, Nakasi R, Nakibuule R. A Review on Automated Detection and Assessment of Fruit Damage Using Machine Learning. *IEEE Access*. Published online 2024. Accessed May 23, 2024. https://ieeexplore.ieee.org/abstract/document/10419325/

[23]. Almomen M, Al-Saeed M, Ahmad HF. Date fruit classification based on surface quality using convolutional neural network models. *Applied Sciences*. 2023;13(13):7821.

[24]. Faye D, Diop I, Dione D. Mango Diseases Classification Solutions Using Machine Learning or Deep Learning: A Review. *Journal of Computer and Communications*. 2022;10(12):16-28.

[25]. Wang C, Xiao Z. Lychee surface defect detection based on deep convolutional neural networks with gan-based data augmentation. *Agronomy*. 2021;11(8):1500.

[26]. Durgapal P, Rana D, Aggarwal S, Gautam A. Defective Fruit Classification using Variations of GAN for Augmentation. In: *2022 IEEE 9th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*. IEEE; 2022:1-6. Accessed May 23, 2024. https://ieeexplore.ieee.org/abstract/document/9986472/

[27]. Han Y, Liu Z, Khoshelham K, Bai SH. Quality estimation of nuts using deep learning classification of hyperspectral imagery. *Computers and Electronics in Agriculture*. 2021;180:105868.

[28]. Melesse TY, Bollo M, Di Pasquale V, Centro F, Riemma S. Machine learning-based digital twin for monitoring fruit quality evolution. *Procedia Computer Science*. 2022;200:13-20.

[29]. Verma R, Verma AK. Fruit Classification Using Deep Convolutional Neural Network and Transfer Learning. In: Balas VE, Sinha GR, Agarwal B, Sharma TK, Dadheech P, Mahrishi M, eds. *Emerging Technologies in Computer Engineering: Cognitive Computing and Intelligent IoT*. Vol 1591. Communications in Computer and Information Science. Springer International Publishing; 2022:290-301. doi:10.1007/978-3-031-07012-9_26

[30]. Ganguli S, Selvan PT, Nayak MM, Chaudhury S, Espina RU, Ofori I. Deep learning based dual channel banana grading system using convolution neural network. *Journal of Food Quality*. 2022;2022. Accessed May 23, 2024. https://www.hindawi.com/journals/jfq/2022/6050284/

[31]. Hameed K, Chai D, Rassau A. A comprehensive review of fruit and vegetable classification techniques. *Image and Vision Computing*. 2018;80:24-44.

[32]. Mu C, Yuan Z, Ouyang X, Sun P, Wang B. Non-destructive detection of blueberry skin pigments and intrinsic fruit qualities based on deep learning. *J Sci Food Agric*. 2021;101(8):3165-3175. doi:10.1002/jsfa.10945

PAPER NAME

FRUIT QUALITY AND DEFECT CLASSIFICATION USING DEEP(chapter)3333_.pdf

AUTHOR

avaneesh

WORD COUNT

10872 Words

CHARACTER COUNT

64020 Characters

PAGE COUNT

50 Pages

FILE SIZE

1.1MB

SUBMISSION DATE

May 28, 2024 3:26 PM GMT+5:30

REPORT DATE

May 28, 2024 3:27 PM GMT+5:30

6% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

- 2% Internet database
- 3% Publications database
- Crossref database
- Crossref Posted Content database
- 3% Submitted Works database

Excluded from Similarity Report

- Bibliographic material
- Quoted material
- Cited material
- Small Matches (Less then 8 words)