**Chapter 11: Smart Technologies for Predicting Shelf Life of Fruits and Vegetables towards Sustainable Agriculture**

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* 1. **INTRODUCTION**

As economic conditions improve, the demand for vegetables, fruits, meat, seafood, and other products continues to rise, indicating a highly favourable market outlook. However, food is also susceptible to corruption and spoiling, resulting in considerable waste and economic losses. Consequently, the significance of food shelf life for consumers and businesses is unequivocal. The Food and Agriculture Organisation of the United Nations reports that around one-third of all food produced for human consumption, or to nearly 1.3 billion tonnes, is lost or wasted globally.

* + 1. **Food Losses in Fresh Produce**

The primary cause of food waste is the degradation and rotting of food during storage or preparation. Fruit and vegetable waste constitutes around 42% of total food waste due to their limited shelf life and vulnerability to environmental conditions during storage and transportation. It is caused by inefficient harvesting, storage, and transport problems, and overstocking within the retail market. In developing countries, most of these losses are post-harvest due to a lack of appropriate infrastructure and cold storage facilities. On the other hand, waste in developed countries tends to be higher at the retail and consumer levels because of over-purchasing and aesthetic standards. People also contribute significantly by spoiling edible parts and storing food improperly. This causes enormous wastage of resources such as water, energy, and labor inputs in production. Some of the key reasons for losses in fresh produce are:

* Not proper harvesting
* Lack of control on temperature control
* Lack of proper handling of produced items
* Improper supply chain management
  + 1. **Key Stages of Food Wastage**

Starting from the production of food items in a farm till the processing of them at the consumer side, the wastage occurs at various states. The contribution of different processes to food wastage is depicted in Figure 11.1.



Figure 11.1 Breakdown of Food Waste from Farm to Consumer.

Farm Stage (11% Wastage):

* A large amount of produce is wasted at the harvesting stage because of wrong methods, poor timing for harvesting, and ineffective labor practices.
* Farm oversupply and failure to respond to market demand frequently translate into late-season edible produce waste.

Post-Harvest and Storage (8% Wastage):

* Lack of storage facilities, temperature control, and quality handling practices cause spoilage during transport and storage.
* Environmental conditions including humidity and temperature changes hasten spoilage of perishable foods such as fruits and vegetables.

Processing (1% Wastage):

* In food processing, inefficiencies in peeling, sorting, and packaging cause wastage that could be avoided.
* Cosmetic requirements cause rejection of fruits and vegetables that are still nutritionally good.

Retail and Stores (6% Wastage):

* Stores are unaware of future shelf life of fruits and vegetables and hence might store the produce in an improper way, resulting in spoilage before time, overstocking, or unnecessary wastage.
* Overstocking, poor inventory management, and storage in retail settings cause wasted produce.
* Produce rejected due to failure to meet cosmetic standards is another major contributor to wastage.
* Lack of certainty regarding the shelf life of goods can lead to incorrect rotation or prioritization of stock, thus causing products to go bad prior to sale or consumption, compounding overall wastage.

Home and Restaurant (10% Wastage):

* Excess purchasing, incorrect storage, and misinterpretation of shelf life at consumer level cause maximum losses.
* Restaurants contribute by generating plate waste and ineffective portion sizes.

Rotting fruits and vegetables also produce methane, a strong greenhouse gas, which helps to fuel global warming. Providing solutions to such losses is instrumental to increasing food security, decreasing environmental damage, and giving supply chains sustainability.

* + 1. **Challenges and Solutions**

Food waste is a worldwide issue, and without early preventative actions, the level of food waste is projected to rise by as much as 70% by 2050 (Chen et al., 2020; Vittuari et al., 2019). It also affects the environment in terms of land, climate change, biodiversity loss, freshwater, marine, and air pollution (Guo et al., 2023).

Shelf life is a significant attribute of the agri-food supply chain that defines marketability, consumer acceptability, and food safety [10]. The shelf life of fruits and vegetables depends on an astronomical number of intrinsic and extrinsic factors such as maturity, firmness, water content, temperature, and bruising. Conventional shelf-life prediction methods depend significantly on visual examination or destructive laboratory analysis, which are subjective, time-consuming, and not suitable for mass production [11]. Thus, objective, automatic, and scalable systems need to accurately predict the shelf life of produce. With the rise of smart technologies, a transformative shift is underway in how shelf-life is assessed, monitored, and predicted.

The food and agriculture sector is undergoing drastic change with the adoption of the most advanced technologies to enhance efficiency and sustainability. The sector contributes to nearly 10% of global GDP and is the backbone of most of the economies, especially in the developing world. Post-harvest losses, inefficiencies in the supply chain, and growing consumer demand for fresh, high-quality products put tremendous pressure on the stakeholders.

Advanced technology and innovations can help the circular economy. Known as Industry 4.0, the fourth industrial revolution has brought technology that improves manufacturing, assists food traceability, raises food safety and quality, lowers food waste creation, and allows total supply chain transparency from farm to consumer. Many examples exist to support this, for instance, works on digital technologies and more particularly, smart sensors, Internet of Things (IoT), and nonthermal food processing, among others.

At every stage of the food supply chain, Industry 4.0 technologies can offer feasible and safe solutions as well as improve food sustainability and sustainable development objectives. Though there is no universal consensus on what technologies fall under Industry 4.0, most research views artificial intelligence (AI), IoT, smart sensors, big data, blockchain, and robotics as fundamental components of Industry 4.0 in agriculture and the food sector. The area of Machine Learning (ML) and sophisticated image technologies also offers significant promise to offer a solution for the creation of precise shelf-life forecasting systems. Advanced ML models like convolutional neural networks (CNNs) can nowadays assess intricate patterns to glean relevant information from photos, which can then assist in forecasting the quality of food in terms of ripeness, disease detection, and general grading

Furthermore, with the advancements in imaging technologies such as capturing infrared images, thermal images, high-resolution images, etc., researchers can utilize these images for the development of more precise food quality grading systems to further predict the shelf life of the food. For example, surface characteristics of food such as color and texture can be captured through high-resolution RGB images, whereas the internal characteristics such as temperature, ripeness indicators, etc, can be captured through thermal imaging devices. Utilizing the proper power of ML models and imaging technologies, a precise and efficient shelf-life detection model can be successfully developed.

Motivated by the power of advanced technologies and the need of the era for the development of accurate shelf-life prediction models for the sustainable agriculture sector, this chapter is focused on providing in-depth details of the shelf-life prediction process. The chapter contains a discussion on the factors affecting the shelf life and indicators for detecting the shelf life. Various traditional ways of shelf line detection methods are also presented. Furthermore, the role of smart technologies for shelf-life detection is discussed, followed by a discussion on different types of ML, deep learning, and hybrid models. A comparative analysis of different existing work is also presented at the end of the chapter to provide a conclusive impact for the readers.

* 1. **SHELF-LIFE PREDICTION: AN OVERVIEW**

The nature of food products, such as fruits, vegetables, deteriorates with time when stored. Consequently, there is a time frame within which these products are acceptable for use. This timeframe, referred to as shelf life, is the time from manufacturing until the point at which the product is not acceptable for utilization. Figure 11.2 depicts the spoilage of apple. In essence, shelf life is the duration within which a food product sustains its important characteristics and remains acceptable for consumption, whether kept by retailers or consumers.



Figure 11.2 Time-Lapse of Apple Spoilage

Industries are trying to achieve the longest possible shelf life for products while keeping costs down and taking into account the realities of how these products are treated by distributors, retailers, and consumers. For example, supermarkets generally expect a product to have at least 75% of its shelf life when it comes into their distribution sites. A short shelf life typically results in customer dissatisfaction, complaints, and ultimately loss of reputation and sales for the brand.

**11.2.1 Factors Affecting Shelf Life**

The shelf life of a food item is determined by various factors, including the natural attributes of the product, environmental conditions for storage and distribution, as well as the packaging. Intrinsic factors, e.g., pH values, water activity (aw), the occurrence of enzymes, microorganisms, and reactive substances, are impacted by the raw materials and process used. Extrinsic factors, on the other hand, encompass environmental conditions such as temperature, relative humidity, light, pressure, and mechanical stresses during handling and transportation. These conditions cause the product to deteriorate at an increased rate. Packaging is also significant, as it can affect extrinsic factors and thus the rate at which a product loses quality. It's very necessary to understand the factors in detail, for better prediction of the shelf life of a particular food.

* + - 1. **Physiological and Chemical Factors**

After harvesting, the fruits and vegetables actively alive, and after which the physiological and biochemical changes continue to take place. These internal changes are major reasons for their deterioration. Some of the key factors under this category of spoilage include:

* ***Respiration Effect:*** Fruits and vegetables respire using oxygen and emit carbon dioxide. Higher respiration rates consume stored energy faster, and thus spoilage occurs quicker, such as green vegetables and berries etc. are highly respiring, which is the reason that they have short shelf lives.
* ***Effect due to Ethylene Production:*** Ripeness of fruits and vegetables occurs due to ethylene, which is a natural plant hormone. Climacteric fruits such as bananas, mangoes, and apples produce huge amounts of ethylene during ripening, and non-climacteric fruits like grapes and strawberries are more susceptible to external ethylene. Proper control of ethylene is required to further control the uneven ripeness throughout the fruit.
* ***Loss of Water:*** Heat causes to loss of moisture and can even lead to dehydration, which causes wilting, shrivelling, and loss of firmness. Green vegetables and herbs that have a high surface area to volume ratio are most critical to this condition.
* ***Microbial Effect:*** Proliferation of the natural microflora on the surface of the produce can result in deterioration, discoloration, and even bring the food into unsound safety conditions.
* ***Activities of Enzymes:*** Softening, degeneration, and browning will be caused by the action of enzymes such as polyphenol oxidase and pectinase.
  + - 1. **Impact of Environmental Factors on Fruit Shelf Life**

Temperature, humidity, wind, and atmospheric pressure are some of the environmental conditions that significantly affect the post-harvest quality and shelf life of fruits and vegetables.

* **Temperature:** The temperature directly affects the respiration and other metabolic activities of food. An increase in temperature increases these activities, which further causes the rapid decay of food. A proper maintenance of temperature is highly recommended, as for certain fruits, the low temperature also causes problems.
* **Relative humidity** is a significant element affecting water loss and deterioration. Elevated humidity levels can diminish evaporation while fostering the proliferation of moulds and bacteria, leading to deterioration. In contrast, low humidity hastens moisture depletion, resulting in dehydration and desiccation. To achieve optimal storage, it is crucial to maintain an appropriate humidity level (about 85-95% for most fruits and vegetables) to inhibit water loss and microbial proliferation.
* **Oxygen and CO2 Levels:** The respiration process of food depends on the level of Oxygen, which affects the deterioration of fresh produce, whereas being a respiratory inhibitor, the concentration of carbon dioxide slows down this process. The ability to monitor oxygen and CO2 levels in storage and transportation environments enables control of the ripening process and prevention of early spoilage, leading to increased freshness of perishable produce.
* **Light Exposure:** Exposure to light, especially ultraviolet (UV) light, can hasten ripening for certain fruits and vegetables. Also, extended exposure to light promotes photochemical decay of nutrients and flavor. Light exposure should be minimized using controlled environments or quality packaging to save the nutritional quality and flavor of produce, mitigating the chance of nutrient destruction and quality reduction.
* **Ethylene Gas:** Most fruits and vegetables give off ethylene, a natural plant hormone that accelerates ripening and aging. Overexposure to ethylene can lead to produce ripened and spoiling vegetables too quickly. By controlling levels of ethylene gas and manipulating the storage environment appropriately, the ripening process can be slowed down, and shelf life can be prolonged, thereby limiting food loss.
* **Wind and Airflow:** Proper airflow ensures the reduction of humidity and ethylene around fruits and vegetables to prevent spoilage. But high wind or inadequate airflow can physically injure the produce while enhancing dehydration. There is a need for proper ventilation to ensure that there are optimal conditions under which the fruits and vegetables stay fresh without getting damaged by too much moisture loss or physical injury.

By knowing and managing these environmental conditions, one can significantly limit the wastage and spoilage of fruits and vegetables. Close monitoring and optimization of conditions along the supply chain mean produce lasts longer, resulting in less waste and a more sustainable food system.

**11.2.2 Indicators for Shelf-Life Detection**

Predicting shelf-life involves identifying quantifiable factors that represent the physiological state of a given product. Freshness, ripeness, and decay are often evaluated using the following indicators:

* Changes in Color: Color changes such as Greenish-yellow coloration for bananas and tomatoes turning red, depict ripening (increasing ripening indices) and usually accompany an increase in the amounts of chlorophyll, anthocyanins, and carotenoids.
* Texture and Firmness: Softening in the texture of fruits and vegetables happens due to the breakdown of their cells. It can now be measured using non-destructive acoustic sensors or, even more advanced, a penetrometer.
* Changes in Aromas: Volatility of certain organic compounds indicates certain stages of aging or development in food products, which can be observed through gas sensors.
* Soluble Solids Content: Commonly referred to as SSC which is often measured in °Brix, SSC is a crucial indicator of the sugar level and sweetness, and maturity of fruits like melons and grapes.
* pH and acidity: Harvest maturity is often indicated by an increase in sugar content and a decrease in acidity with the progression of fruit ripening. Changes in pH can also monitor the optimal harvest and consumption windows.
* Visual signs of Spoilage: Signs indicative of Microbial and chemical in nature spoilage include mold growth, discoloration, and exudation (liquid leaking) as well as abnormal odors.

The detection and monitoring of these indicators through manual or smart technologies is highly necessary for the development of shelf-prediction models.

* 1. **SHELF-LIFE PREDICTION: METHODS**

Managing the quality, safety and marketability of fresh produce requires accurate prediction of its shelf life. It allows all actors in the supply chain—from growers to sellers—to make proper decisions regarding the harvesting, storage, transportation, and distribution. Over time, methods for predicting shelf life have advanced from simple empirical estimation to complex predictive technological models. This essay describes the primary traditional, contemporary, and modern approaches used in estimating the shelf life of fruits and vegetables.

* + 1. **Traditional Methods for Shelf-Life Prediction**

Conventional methods of estimating the shelf life of fruits and vegetables are done on age and are basic, yet still applicable for basic quality control. These are fundamentally subjective human observation and basic instruments to ascertain the freshness, maturity and general status of the product. These techniques do not have the precision or the scalability of contemporary techniques, but offer a fast and cheap means to ascertain quality, particularly in small and medium-sized enterprises and settings where advanced technology is inaccessible.

Some of the most typical old ways are:

* **Visual examination:** Visual examination of observable signs of ripe, rot, or rot. For instance, bananas and apples ripen, and their colour changes. Bananas become yellow from green, and apples become red or yellow based on variety. Exterior surfaces, bruising, or discoloration are usually utilized to determine the status of fruits, which foretell how long they will be fresh. Aside from colour, size and shape changes may also be taken as indicators of aging or maturation. For instance, when cucumbers dehydrate, they will shrink or get muddy, and the tomatoes may become soft at the stem's edge at the stem's edge. When testing fruits like tomatoes and peaches, an individual can squeeze the fruit to check for softness and strength, which are important signs of maturation or spoilage. Festivals are typically related to freshness, but excessive softness and creaks mean that the product has overrun or begun.
* **Odour examination: S**mell testing is commonly employed to spoil it. Odors like fermented and acidic odours are clear signals that the fruit has already reached its expiration date and can no longer be consumed. For instance, the strongly fermented odour of spoiled bananas and apples shortens the time because they already give off a sign of fermentation or development of microbial growth. It involves separating fruits and vegetables according to their appearance. These include obvious flaws like size, colour, staining, cutting, cracking, and others. For instance, sorting of tomatoes will be selected to be more endurance when sorting tomatoes with skin and uniform colours but cracked and split ones are set aside since defects hasten decay. Sorting can also be utilized to approximate the maturity or ripeness of a commodity. Texture changes, wrinkling, or softening of the case or alteration of the colour of the seeds may signal maturity. In some instances, split or cracked skins occur in mature tomatoes. This means that the fruit is too old to consume and is most likely to reach the end of durability.

Traditional methods tend to be quick, cost-effective and effective but with troublesome constraints. They depend on human instinct, yet they can be inconstant and arbitrary, particularly in judging goods with alternative sources or conditions. Traditional methods do not identify latent faults or corruption which is unseen and intangible at the surface level. In spite of these limitations, conventional technologies still play a crucial role in the evaluation of durability, particularly small markets and not available advanced tools and technologies. Thus, these techniques are valuable supplements to a more contemporary and quantitative method for establishing the durability of fruits and vegetables.

**Conventional Methods:**

* **Destructive and Chemical Testing:**

Chemical tests involve measurements of changes in chemical bonds in foods, like pH values, acids, and oxidized products. Through tracking these chemical changes over time, you are able to gauge the quality of your food and know their longevity. This kind of test is usually used for irregular shapes, like canned goods and packaged snacks.

One of the most significant advantages of chemical testing is that it can deliver precise, objective and quantitative information regarding the status of a food product. Nevertheless, it involves special equipment and expertise and might be more costly than other methods. Chemical testing might not detect any form of corruption. These methods utilize simple scientific principles to deliver more reproducible and more consistent measurements.

**Moisture Content:** Water loss recording for measuring freshness.

**Firmness Tests:** Penetrometers to test the texture of fruits like apples.

**pH Measurement:** Measuring acidity to assess ripeness or spoilage.

**Sugar Content (Brix Test):** Capturing sweetness as fruits ripen.

**Drawback:** Test sample cannot be reused.

* **Respiration Rate:**

Fruit and vegetables (F&V) are living tissue and have high respiratory rates that play a significant role in determining durability. Respiration eliminates oxygen and expels carbon dioxide, resulting in the loss of nutrients. Climatic fruits like mangoes and bananas exhibit peaks of respiratory rates when they reach maturity, whereas non-permeable fruits have a steady respiratory rate. Altered or controlled air-mediated regulation of respiratory rates can slow down metabolic activities and enhance durability.

* **Microbiological Spoilage:**

F&V is prone to microbial rot because it contains water and nutrients. Microorganisms invade wounds and wear, leading to deterioration without changing appearance. Sanitary handling and proper packaging and storage conditions are needed in order to minimize microorganism growth and expansion of freshness.

* **Moisture Loss:**

Water loss largely results in weight loss in F&V, wild and structural breakdown. It impacts surface-to-volume ratio, skin characteristics, and environmental conditions like atmospheric humidity and temperature. Storage by maintaining proper packaging and high relative humidity (85%) could minimize this issue.

* **Ethylene:**

Ethylene (C2H4), a fruit growth hormone, regulates aging and aging of fruits and plant varieties. Climatic fruits have ethylene induced to ripen at a level of merely 0.1-10 ppm, while unwanted exposure triggers spoilage. Ethylene even at later stages of non-permeable fruits stimulates respiration and production. In our project, ethylene monitoring is employed to learn about durability and maximize storage conditions that reduce spoilage and wastage. Early treatment of chromonic fruits prior to maturation will cure durability, whereas ethylene management in non-climate fruits will halt maturation. Through the tracking of ethylene mirrors in real time, you can minimize corruption by 25%. This will lead to fresh products and minimal waste. This technology plays a significant role in fighting food sustainability and supply chain sustainability.

Older technologies are usually quick, effective and cost-effective, but not without strict limitations. They are based on human judgment, but they can be subjective and unreliable, particularly when assessing products from different sources or under different conditions. These approaches do not identify concealed defects or corruption that cannot be detected or sensed on the surface. Notwithstanding these disadvantages, conventional techniques are still essential in the estimation of durability, particularly small markets and unavailability of advanced technology and tools. These techniques thus are valuable additions to a more quantitative and new age approach in determining the durability of fruits and vegetables. The methods are beneficial but tend to get absorbed by the inability to capture subjectivity, product variety changes, and environment variability in real time.

* + 1. **Modern Approaches for Shelf-Life Prediction**

Present practices for determining shelf life for fruit and vegetables have an intense concentration on non-destructive approaches to analyse the product without physically degrading or impairing its quality. Advanced image and sensing techniques, including RGB imaging, spectroscopy (hyperspectral, Raman, and NIR), thermal imaging, and X-ray imaging, are utilized in these techniques to scan internal and external features such as colour, texture, moisture, and structure. In contrast to the conventional destructive testing with sampling and cutting, the non-destructive methods keep the produce intact for sale or additional processing. Machine learning algorithms, especially convolutional neural networks (CNNs), are incorporated into these methods to process images or data collected, providing precise predictions for ripeness, spoilage, and shelf life left. These innovations not only increase accuracy but also render the process scalable and appropriate for real-time monitoring in industrial applications, minimizing food waste and enhancing supply chain efficiency.

* **Spectroscopy Techniques:**

Spectroscopy methods are non-destructive processes that examine the interaction between electromagnetic radiation and fruits and vegetables in order to assess their biochemical and molecular characteristics. Spectroscopy measures important indicators like moisture, sugar levels, acidity, and internal defects that play a crucial role in shelf life. Through the capture of chemical composition changes due to ripening or decay, spectroscopy gives detailed and accurate observations of produce quality. The following are three important sub-techniques that are commonly employed in shelf-life prediction:

* **Near-Infrared (NIR) Spectroscopy:**

NIR spectroscopy analyses the absorption and reflectance of near-infrared light (700–2500 nm) by produce to quantify internal parameters such as water content, sugar concentration, and acidity. It is very efficient for monitoring the ripening of fruits and vegetables by identifying starch-to-sugar conversion and water loss. Although swift and non-invasive, its low penetration depth makes it most appropriate for small or thin-skinned produce.

* **Raman Spectroscopy:**

Raman spectroscopy examines molecular vibration by measuring the scattering of monochromatic light. It is very sensitive to pigments like chlorophyll and carotenoids, which give information about ripeness and structural integrity. It, for example, identifies biochemical changes in cell walls while produce is ripening or spoiling. It needs controlled environmental conditions to perform at its best and is costlier compared to others.

* **Hyperspectral Imaging (HSI):**

HSI integrates spectroscopy and imaging for gathering spatial and spectral information over a range of wavelengths. HSI detects chemical compounds and early signs of spoilage such as fungal infection or bruising before they can be seen. HSI is superior to map moisture distribution and find changes in texture and composition that are subtle but has to undergo sophisticated data processing and is more expensive than less complex imaging techniques.

* **X-Ray Imaging:**

X-ray imaging is an advanced, non-destructive technique that has become a key tool for forecasting the longevity of fruits and vegetables. Due to the application of electromagnetic waves with permeable energy, it offers precise internal structure data without damaging the sample. This technique is ideal for identifying concealed defects like bruises, cavities, cracks, and empty cavity, which are significant markers of corruption and quality degradation. Unlike surface-based methods, X-ray imaging analyses the sound within fruits and vegetables and breaks through outer attributes like colours and textures to enable improved assessment. For instance, you can identify apples, avocados, and citrus bruises. In addition, X-Ray imaging can effectively track structural changes in ripening. B. Microbial activity that can soften or form the cavity and degrade the product's durability. This plant is especially helpful for high quality or loose products that are meant to be stored or transported for a long time. When combined with machine learning algorithms, the applications of X-Ray imaging are further enhanced. Folding (CNNS) and advanced models can analyse X-ray images to receive significant features like density changes and structural flaws. These features enable automatic identification of the aging stage and precise identification of remaining durability. In addition, X-ray imaging for industrial production is centrally significant, enabling X-ray images to be utilized in automated sorting and sorting systems to look for quality products in the market. The price of devices and radiation security measures can render small operations challenging to finance them.

Reading X-ray images also demands sophisticated software and technical expert knowledge, which can lead to operational complexity. However, through continuous innovations in imaging technology and machine learning, these issues are overcome, rendering X-Ray imaging less expensive and more adaptive to a wider array of applications. The capacity to reveal flaws, pursue structural alterations, and provide trustworthy forecasts in terms of longevity is a golden asset for contemporary agriculture and supply chain management. In combination with technological development that continually enhances ability, X-imaging is central to cutting food loss, optimizing storage and transport, and providing consumers worldwide with a regular, high-quality product supply.

* **Thermal Imaging:**

Thermal imaging is a new, non-destructive technique that has transformed the measurement of fruit and vegetable durability. It involves the use of infrared technology to capture variations in thermal patterns and temperature, conveying crucial information regarding the physiological and structural integrity of the product. Technology is able to identify internal conditions like bruises, cavities, cracks not visible to the human eye or conventional RGB imaging. Moreover, thermal imaging makes it possible to capture vital parameters that have direct contribution to durability, tracking the maturation stage, and loss of loss and moisture.

One of the key benefits of thermal imaging is its sensitivity to subtle temperature changes caused by metabolic activity like respiration and microbial growth. Such activity is an indicator of ripeness and dryness or incipient rot. Thermal imaging, for instance, can track elevated respiration rates in climatic fruits like bananas and mangoes to categorize maturation stages and forecast remaining durability. It also aids you in identifying moisture losses in dense vegetables and root vegetables and identifying the quality decline stages. More sophisticated versions like the folding seller neural network (CNNS) analyse the thermal patterns to classify products once they have ripened or are spoiled, with the algorithm prediction estimating durability highly accurately. This pairing makes possible automated, scalable, real-time quality checking, and that is why thermal imaging is suitable for industrial purposes like sorting, classification, and cooling chamber management. Also, your contactless saves nature, an unscathed product available for sale or consumption.

As many advantages, thermal imaging is not always challenging. For instance, interpreting sophisticated thermal data entails sophisticated image processing and machine learning. Nevertheless, ongoing technical advances bridge these barriers, rendering this technique more effective and accessible. As technology has improved, thermal imaging has become a valuable instrument for sustainable and optimized farming techniques to the advantage of farmers, traders and consumers.

* **RGB Imaging:**

RGB imaging is a non-conclusive, non-destructive way of estimating the fruit and vegetable shelf life. It takes images of surface features like colour, texture, and shape and offers excellent references to the onset of aging, quality, and corruption. RGB imaging is highly applicable for the mature classification task, since colour change in fruits and vegetables like bananas, tomatoes, and strawberries are effective indicators of freshness and decay. In addition, RGB imaging is able to detect decay via not just moisture loss and shrinkage of products like cucumbers and succulent vegetables, but also via visible defects like discolouration, mould and wrinkles. One of the key benefits of RGB imaging is that it is relatively easy and affordable. Standard digital cameras and machine learning algorithms supply scalable applications for real-time monitoring and quality control within production environments. Machine learning models, such as folding fish networks (CNNS), improve the process by automatically deriving properties from RGB images and sorting fruits and vegetables following maturation or melting. This is achievable through precise prediction of durability, eradication of human error, and precise prediction of waste reduction and making supply chains efficient.

Nonetheless, RGB imaging has its drawbacks. Surfaces can be scrutinized and internal injuries like bruises and cavities can be neglected. It also reacts to external conditions like illumination, which can alter the precision of colour-based measurements. Nonetheless, such issues are released with ongoing developments in multimodal fusion, such as machine learning, techniques of data expansion, and hyperspectral imaging. RGB imaging is an effective and affordable way to foresee durability with optimal compromises in between accuracy, scalability and affordability. His capability of decision on true time turns out to be an important commodity for today's food supply chains and farming in eliminating removal, tightening and guaranteeing fresh goods to customers.

The various types of durability forecast the advantages and disadvantages. A comparison of the various approaches is illustrated in Table 11.1. Asmit

**Table 11.1: Comparison of Methods:**

|  |  |  |  |
| --- | --- | --- | --- |
| **Criteria** | **Traditional** | **Conventional** | **Modern** |
| **Accuracy** | Low, subjective | Moderate | High |
| **Scalability** | Limited, labour-intensive | Moderate | High |
| **Cost** | Low | Moderate | Varies (can be high initially) |
| **Time** | Immediate but imprecise | Requires sample preparation and testing | Fast with automation |
| **Sample Integrity** | Fully intact | Partially destructive | Fully intact |

* 1. **SMART TECHNOLOGIES FOR SHELF-LIFE PREDICTION**

Smart methods rapidly transform the monitoring and forecasting of fruit and vegetable shelf life. Unlike conventional techniques based on static and ex-hoc assessment, smart technologies make possible real-time, non-invasive, and very accurate forecasting through the combination of records, data analysis, and automation. These technologies are particularly useful in complex, perishable supply chains where early identification of quality closures avoids losses, maximizes logistics, and maintains food safety.

Here you will find the most significant intelligent technology applied to foresee the life of fresh products.

* Internet of Things (IoT) technology played a crucial role in the real-time monitoring of environmental conditions influencing product durability. For instance, an IoT-based system incorporating temperature and moisture sensors was used to monitor memory environments. This enables early detection of rot and more precise prediction of durability.
* We used artificial intelligence (AI) and machine learning (machine learning) models to forecast the shelf life of different foods through the analysis of extensive data records including environmental conditions and product attributes. These models are capable of recognizing intricate patterns and making better predictions than conventional approaches. For instance, deep learning models were developed to forecast browning in fresh-cut salads. This is a novel quality of quality by examining the product's picture.
* Biosensors have been constructed for certain chemical indicators like spoilage. B. Volatile organic compounds (VOCs). They give quick and sensitive detection and permit timely intervention to avoid quality degradation.
* We explored blockchain technology to enhance traceability and transparency in the food supply chain. By documenting and exchanging information on conditions and product processing, blockchains can enable more precise predictions of durability as well as verify information integrity.

In total, these clever technologies provide really wide-ranged prediction of durability based on real surveillance, advanced data analysis and secure information exchange in order to facilitate better management of fresh products.

* 1. **Machine Learning Approaches for Predicting Shelf Life of Fruits and Vegetables**

Machine Learning (ML) algorithms have revolutionized the assessment of fruits and vegetables. Such a process employs both structured and unstructured data to analyse endogenous and exogenous factors influencing product spoilage. From simple models to sophisticated deep learning models, ML techniques were employed to estimate durability with increased accuracy, scalability and robustness. In this section, such processes are explained, including their evolution, and describes how the horizon of the future will expand.

* + 1. **Conventional Machine Learning for Shelf-Life Prediction**

Conventional machine learning models rely on predetermined attributes derived from generation functions like color, texture, weight, and biochemical characteristics.

* **Support Vector Machine (SVM):** SVMs were widely employed for the purpose of classification. Texture features, colour histograms, and weight deviations are inputs to SVM classifiers to separate fresh products from largely decorated or spoiled classes.
* **Random Forests:** A robust ensemble algorithm used for multi-feature analysis of predictors of shelf-life. Features such as moisture content, respiration rate, and amounts of ethylene emissions are utilized to train the model.
* **K-Nearest Neighbours (K-NN):** This is a model that is beneficial for small data records and categorizes fruits on the basis of similar samples according to similarity. It is utilized for operations like recognition of levels of maturation and classification of periods of durability.
* **Naive Bayes Classifier:** Probabilistic model based on Bayes' theorem with independent properties. Good for fast and straightforward classification tasks, i.e., classification of fruits based on pre-defined displacement measurements.

Asmit

* **K-Means Clustering:**

An unsupervised algorithm for splitting data into groups based on similarity. Segregating fruits by ripeness level or identifying spoilage patterns.

**11.5.2 Deep Learning Models for Shelf-Life Prediction**

Deep learning (DL) has really promoted shelf-life prediction by making feature extraction automatic and dealing with massive amounts of data. The models work very well when used together with image technologies such as RGB and thermal imaging.

* **Convolutional Neural Networks (CNNs):** CNNs have widely been utilized for extracting spatial features from fruit images. Features including colour gradients, surface texture, and bruising are recorded utilizing spectrogram-like representations of RGB and thermal imagery.
* **Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs):** These models learn temporal patterns in sequence data, for example, variation in respiration rates or temperature as a function of time.
* **Transformer Models:**

Recent breakthroughs such as Vision Transformers (Vites) are being investigated for predicting shelf-life by processing sequential image data.

**11.5.3 Hybrid and Emerging Models**

Shelf-life detection hybrid models merge various methods, e.g., machine learning algorithms, imaging techniques, and environmental sensors, to improve prediction accuracy. These models bring together the advantages of deep learning, e.g., Convolutional Neural Networks (CNNs), and analytical methods like regression or Bayesian methodologies to handle different types of data. Hybrid models apply RGB, thermal, and hyperspectral images to external and internal quality testing, with environmental conditions such as temperature, humidity, and ethylene concentrations to estimate shelf life. By fusing information from multi-modal sources, they achieve a more holistic and accurate prediction. Such models are superior in addressing uncertainty and providing flexibility for different conditions across supply chains. They are better than individual models by enhancing robustness and scalability, with a great reduction in food wastage. Hybrid methods are best suited for real-time tracking, enabling stakeholders to have actionable insights to maximize storage and distribution networks for perishable commodities.

* **Transfer Learning:**

Transfer learning is a machine learning process where a model is developed for a task to carry out related but distinct tasks. Rather than training the model from the start, Transfer Learning leverages the knowledge within an already developed network. This is typically trained on large and diverse data sets. Transmission learning is achieved by fine-tuning the model by rewriting its parameters with smaller domain-specific data sets. For instance, trained models can be adjusted in ImageNet, a big image database, to label medical images and interpret fruit durability from visual abilities. Thermal imaging transfer learning to predict fruit durability. Lightweight prefabricated CNN models like squeeze net, MobileNETV2, and Shuffle-net were utilized for fruit classification based on the available fresh levels. Thermal imaging was employed to analyze crucial characteristics like interior textures, bruising, and other quality factors, creating a non-destructive and useful way of evaluating durability. Utilizing preview models like MobilentV2, Squeeze Net, Shuffle-Net, etc., this work shows how effective characterization extraction of classes and fruit statements can be conveyed after the remaining useful life. This approach greatly minimizes computational burden and time from the training model's point of view right from the beginning, but ensures high precision. The study shows the significance of structured models in agricultural methods, which means that models requiring minimal retraining can be adapted to particular problems like fruit classification and durability estimation. Thermal imaging performed better when capturing internal quality characteristics compared to RGB imaging. Shuffle-Net was the best model for application in practice from among tested models, being efficient and very accurate. Techniques like data expansion were applied in order to enhance model adaptability and trustworthiness. This technique solves some of the greatest problems of cutting food through enhancing product separation based on freshness, enhancing storage practices, and enhancing better supply chains. Through the combination of thermal imaging and transfer learning, studies offer sound and scalable technologies for opportunities of reducing postharvest losses. The framework allows for the possibility of enhancing the efficiency and sustainability of agricultural resources.

* **Bayesian Neural Networks:**

Bayesian Neural Networks (BNNs) provide a probabilistic solution for predicting durability with uncertainty. In contrast to point estimates for regular neuronal networks, the distribution of BNN parameters (weights) is predicted, allowing us to predict the size associated with prediction uncertainty. This is especially useful when predicting fruit durability. In this case, inherent randomness can result in considerable unpredictability in ambient conditions, internal fruit properties, and sensors. The weight distribution at the back enables BNN to deliver not just the most probable forecast of durability, but also the confidence interval or prediction probability. For instance, we can estimate that the mangoes belong to the "RUL-5" category, which has a 70% probability of a chance, and the "RUL-4" category, which has a 30% probability of a chance. A probabilistic version like this makes way for sensible decisions. B. Assignment of boundary lines to storage conditions from risk assessments. For instance, if the image has inconsistent lighting, or if the fruit is jammed in different environmental conditions, BNN can actually incorporate this uncertainty into its output. This capability can be utilized to make prediction systems more robust, resilient to real variations, and prevent potential misclassification and subsequent food waste.

* **Reinforcement Learning (RL):**

Increased Enhancement (RL) can be applied to build a process for establishing the remaining useful life of a fruit. RL differs from monitoring learning with agents when labeled data records are utilized, trying out environments and learning to get rewards or penalties for feedback. As for the matter of retention life, RL agents can test fruit-related knowledge, including intrinsic properties like texture, color, and heat behavior as well as extrinsic environmental parameters like temperature and air humidity within the storage environment. The RL approach gives conditions, actions, and rewards their specifications. The condition may be a present observable attribute of the fruit. B. Its RGB or thermal image data. Actions can forecast intervention suggestions like particular types of durability ("remaining useful lifespan of 5 days") or optimizing storage conditions. Rewards are made up to encourage accurate predictions and penalize miscarriage. For instance, agents can accurately predict that there will be mangoes in the "Rule-3" stage and reward them if they penalize them for underestimating freshness. With time, the decisions can be made optimal not only for estimating durability but also for suggesting steps to minimize food wastage. This is a dynamic and quick-response strategy especially when information is limited or when the system must be generalized under a wide range of conditions, such as varying types of fruit and storage conditions. By incorporating RL into your project, it complements other transfer learning methods to give a strong framework for surmounting the complexity of predicting durability.

Abhay

**11.4 COMPARISON OF EXISTING APPROACHES**

Machine learning models (ML) proved highly efficient in tackling some issues of predicting fruit and vegetable longevity. One such usage is that ML models like folding networks (CNNS) and ML models like support vector machines (SVMs) like SVMs are capable of recognizing levels of maturity through colour changes and texture modification with over 90% precision. For instance, CNNS strawberries or tomatoes are grouped based on the evolution of the colour, a good indicator of freshness. Another major application is forecasting remaining useful life (rules) of fruits and vegetables, particularly fruits like bananas and avocados. We forecast long-term short-term networks of durability (LSTMs) that evolve over time by exploring temporal variation, i.e. H. respiratory rates and ethylene release. It is discernible but impinges on durability. These techniques are not only used for the prediction of duration of durability, but also for enhancing general quality control in farm practices. For instance, Shenoy et al. (2023) illustrated how deep learning algorithms automate the process of fruit sorting based on maturation and optimize supply chain management. This functionality enables better inventory checks, particularly in cooling storage environments. Real-time storage predictions that are built into IoT sensors maximize the sales of perishable commodities and rank goods with short shortages for sale. Such practices also find their applications in digital trade and e-commerce to forecast and convey the freshness of fruits, higher consumer confidence, and minimized returns due to corruption. Reflection. (2020). These innovations are a significant step in reducing food loss and enhancing the efficiency of the agricultural supply chain.

**IoT and Deep Learning Integration:** The combination of DL models and IoT sensors (Internet of Things) allows real-time monitoring of fruit quality. Real data such as temperature, humidity in the air and light pollution can be combined with visual data in order to enhance durability estimation. Bhole & Kumar (2021) proved the capability of thermal imaging combined with CNN models for real-time prediction of fruit quality. This technique is highly applicable in cold rooms where observation of real thyme is necessary to achieve freshness of stored plants.

**Real-time applications and object detection:** Sanath S. Shenoy et al. (2023) applied two models of object recognition, faster R-CNN and Yolo, to forecast banana durability. It has been discovered that Yoro is more efficient, quicker, and can be implemented in real-world applications of refrigerated retail and storage. This shows that establishing a balance between model efficiency and accuracy in the development of systems for real-time monitoring is crucial. (Abhay)

**Table 11.2: Review of Existing Related Work on Machine Learning-Based Shelf-Life Prediction**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Approach** | **Authors** | **Task** | **Dataset/Features** | **Methodology** | **Performance** | **Analysis** |
| **SVM** | Smith et al. (2020) | Ripeness classification | RGB images, texture-based features | SVM classifier with RBF kernel for separating ripe vs. unripe classes. | 88% accuracy on mango datasets | Effective for binary classification; requires careful feature engineering. |
| **Random Forest** | Lee et al. (2021) | Shelf-life prediction | Temperature, humidity, moisture content | Random Forest with feature importance analysis to predict shelf-life duration. | Achieved 85% acc. for strawberries under controlled conditions | Robust to noisy data; interpretable results but computationally intensive. |
| **k-NN** | Patel et al. (2019) | Spoilage stage identification | Pre-processed RGB images, colour histograms | Distance-based classification of spoilage stages. | 80% accuracy on banana datasets | Simple but inefficient for large-scale data due to high computation. |
| **CNN** | Wang et al. (2022) | Ripeness and spoilage detection | RGB images for colour and texture, thermal images for internal defects | Deep CNN architecture with convolutional and pooling layers for feature extract. | >95% accuracy on mango and banana datasets | Excellent at capturing spatial patterns but requires large labelled datasets and GPU resources. |
| **Transfer Learning** | Kim et al. (2023) | Shelf-life prediction | Pre-trained MobileNetV2 fine-tuned on fruit datasets | Fine-tuning of pre-trained models to predict remaining useful life (RUL). | 92% accuracy with minimal labelled data | Reduces the need for extensive datasets; risk of overfitting if not tuned correctly. |
| **LSTM** | Gupta et al. (2020) | Temporal modelling of ripening | Time-series data (temperature, ethylene levels) | Sequential analysis of changes over time to model ripening and spoilage patterns. | Achieved >90% accuracy for avocado datasets | Effective for time-series data; high computational cost and memory usage. |
| **Hybrid CNN-LSTM** | Kumar et al. (2022) | Shelf-life prediction | RGB images + time-series data | Combines CNN for feature extraction and LSTM for temporal pattern recognition. | 94% accuracy on combined datasets | Integrates spatial and temporal features effectively; requires significant computational power. |

* 1. **CONCLUSION AND FUTURE DIRECTIONS**

Good evaluation of new products in durability is crucial to minimize post-harvest losses, enhance supply chain efficiency, and respond to global nutrition security concerns. In this chapter, we discussed different approaches to machine learning, such as SVM, random forests, and other deep learning architectures. B. CNNS and LSTMS. RGB and thermal imaging, in addition to these models, along with RGB and thermal imaging, possess tremendous potential to automate maturation and rot ability. Transfer learning and geese also mitigate data shortage issues and enhance solution scalability. With or without new improvements in classical models to generate sharper results, how in resource beat environments remains always helpful. Further work in multimodal integration of data and above integration of a strong scalable estimation system towards durability. These technologies enable the agricultural sector to perform responsible and precise treatment of products that help minimize food waste and maximize resources. The highly advanced strategy employs deep learning colour tasks like generative controversial networks (Goose) to simulate real-world conditions and enhance durability prediction accuracy.

Darshit

**References**