International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
ISSN: 3068-272X www.ijdim.com Original Research Paper

REAL TIME SHELF LIFE PREDICTION OF FRESH PRODUCE USING CNN BASED TEMPERATURE ANALYTICS

G. S. Sundeep Kumar[1], Himaja[2], Jella Siddartha[2], M. Venkata Sree Nayan[2], L. Bhadru[2]
[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (AI&ML)
[1,2]Sree Dattha Institute of Engineering and Science, Ibrahimpatnam, 501510, Telangana.

Received: 09-07-2025 Accepted: 23-08-2025 Published: 30-08-2025

ABSTRACT

India is one of the largest producers of fruits and vegetables globally, contributing about 14% of the world's total production. However, a significant portion of this produce—approximately 30–40%—is lost due to inefficient storage and transportation systems, resulting in an economic loss of ₹92,651 crores. The objective of this project is to develop a deep learning-based model that uses temperature simulation data to accurately predict the shelf life of fresh fruits and vegetables, thereby enabling optimized transport and storage conditions. The proposed system employs deep Convolutional Neural Networks (CNNs) to predict how long produce will remain viable based on temperature data collected during storage and transit. This approach supports decision-making aimed at reducing spoilage and enhancing logistics. Traditionally, shelf-life prediction relied on static temperature guidelines, manual inspections, and general estimations based on historical data—methods that often led to inaccuracies and higher wastage. These conventional systems lack the precision and adaptability needed for efficient management, resulting in significant post-harvest losses. Reducing these losses is critical to ensuring food security, especially in a country like India. Machine learning models offer the potential to make precise shelf-life predictions by incorporating real-time environmental data, thereby minimizing waste, improving economic returns, and ensuring fresher produce reaches consumers. A deep learning model trained on temperature patterns can provide real-time shelf-life estimates, allowing stakeholders to make informed decisions regarding storage adjustments and route optimization. Additionally, the AI system can generate alerts for optimal consumption periods and transportation planning. This solution stands to significantly enhance efficiency and reduce the costs associated with spoilage.

Keywords: Shelf-Life Prediction, Deep Learning, Convolutional Neural Networks (CNNs), Temperature Simulation Data, Post-Harvest Loss Reduction.

1. INTRODUCTION

The global fruit and vegetable supply chain faces significant losses due to improper handling and suboptimal storage conditions. According to the Food and Agriculture Organization (FAO), around 45% of global fruit and vegetable production is lost or wasted annually, mainly because of spoilage during post-harvest handling, transportation, and storage. Temperature fluctuations during these phases play a critical role in reducing shelf life by accelerating biochemical changes and microbial growth, leading to early spoilage. This not only impacts profitability for farmers and distributors but also contributes to food insecurity and environmental degradation through the waste of vital resources. Maintaining the cold chain is thus essential to minimizing perishability. Studies have shown that even short periods of exposure to non-optimal temperatures can reduce shelf life by up to 50%. For instance, strawberries that typically last 7 days at 0°C may spoil in just 2 days at 10°C. While the economic loss from such degradation in the United States exceeds $15 billion annually, the problem is even more acute in developing countries, where poor infrastructure worsens post-harvest losses. In response, the ability to collect high-resolution

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
ISSN: 3068-272X www.ijdim.com Original Research Paper

temperature data through sensor technologies and IoT-based cold chain systems has opened new possibilities for tracking environmental conditions and predicting spoilage.

Despite these advancements, traditional self life estimation methods remain static and fail to accommodate the variability inherent in real-world logistics. In this context, real-time forecasting tools based on temperature data are increasingly essential, especially for exporters aiming to expand across longer routes. Large-scale operations like those of Dole Food Company, Del Monte, and Fresh Delights face logistical challenges in ensuring freshness throughout global supply chains. Even minor deviations in temperature during transit can result in spoilage, prompting the need for predictive analytics that go beyond fixed laboratory-based estimates. Similarly, major retail chains such as Walmart, Tesco, and Carrefour depend on precise inventory management to balance availability and quality. Integrating temperature-based forecasting into their warehouse management systems (WMS) allows them to predict spoilage, prioritize inventory based on freshness, and enhance customer satisfaction. Moreover, agri-tech startups like AgroStar, CropIn, and Intello Labs are leveraging AI and embedded sensors to provide real-time insights that guide transportation decisions, reduce spoilage risk, and support sustainability.

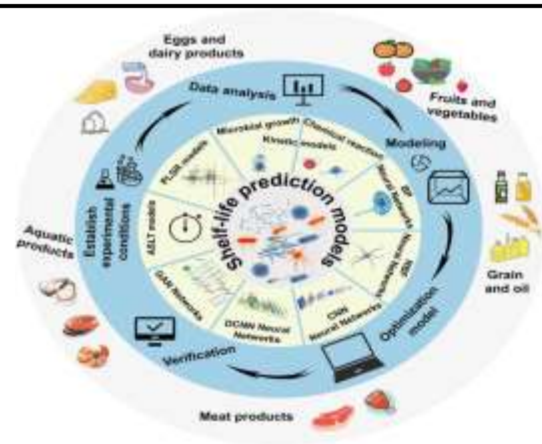


Fig.1: Shelf-Life Prediction Model Framework for Food Products

The key challenge lies in accurately estimating the remaining shelf life of fresh produce during transit and storage, where current fixed-value methods are insufficient. These generic estimates are based on static lab conditions and ignore real-time environmental variables like temperature and humidity fluctuations. As a result, supply chain stakeholders often detect spoilage only after delivery, reacting too late to prevent losses. Furthermore, disruptions such as equipment failures or power outages are not accounted for in conventional models. This lack of integration between time-series data and predictive analytics creates a technological gap that limits the effectiveness of cold chain logistics. Bridging this gap with a robust, adaptable forecasting model is critical to improving operational decision-making and ensuring product quality upon arrival.

Developing a temperature-based self life prediction system offers transformative benefits for the agricultural supply chain. It empowers stakeholders across the value chain—from farmers to retailers—with actionable insights to make informed decisions regarding harvesting, storage, and transport. Such a system reduces food waste, enhances quality control, and boosts efficiency through timely interventions, such as rerouting or reprioritizing shipments. In doing so, it also supports environmental sustainability by reducing the waste of water, energy, fertilizers, and labor embedded in spoiled produce. Furthermore, this predictive capability contributes to food security by extending the viability of produce, especially in regions with limited infrastructure, allowing more equitable access to food and improving resilience against supply disruptions.

The primary research objectives of this study include analyzing traditional time-series models such as ARIMA for temperature-based self life forecasting and developing a deep learning model using Convolutional Neural Networks (CNN) to handle variable-length sequences of temperature data. This CNN-based regressor will be evaluated for its accuracy, adaptability, and robustness in real-world conditions and compared against conventional approaches to assess its superiority in dynamic logistics environments. The proposed system offers several advantages, including reducing post-harvest losses, enabling dynamic decision-making, improving inventory and quality control, ensuring better consumer satisfaction, and supporting food safety compliance. It also minimizes resource waste, reduces financial risk, and encourages the digital transformation of small and medium enterprises. Furthermore, its scalability allows adaptation to different crop types through model retraining.

In terms of applications, this system is beneficial in a variety of sectors. It can be used in long-distance export logistics to plan optimal delivery schedules and refrigeration strategies. Retail warehouses can use it to dynamically rotate stock based on predicted freshness, while online grocery platforms can ensure product quality during last-mile delivery. Logistics providers can leverage real-time data for routing decisions, and cold storage facilities can automate dispatch based on self life projections. Additionally, food processing industries, regulatory bodies, and food banks can use the system for quality assurance, compliance audits, and redistribution of near-expiry items. Agri-tech R&D firms may also find it valuable for designing advanced packaging and preservation solutions. Overall, this research aims to revolutionize post-harvest management by making self life prediction more intelligent, accurate, and actionable.

2. LITERATURE SURVEY

The goal of the paper [2] was to detect intrinsic features of fruits such as internal defects, bruises, texture, and color and classify fruits according to their remaining useful life (RUL). The study uses the data of 'kesar' mango [3]. It uses thermal imaging to determine the intrinsic values of fruits in terms of temperature. Furthermore, a transfer learning approach is combined with thermal imaging techniques to enhance the accuracy of fruit shelf-life prediction. The study compares three lightweight CNN-based models, namely SqueezeNet [4], ShuffleNet [2], and MobileNetv2[5]. The results demonstrate that the highest achievable accuracy of up to 98.15% is obtained. It is also observed in the study that using thermal images resulted in a significant reduction in training time. In the paper [6], the aim is to predict the ripeness level and CO2 respiration rate (RRCO2) [7] of the 'kesar' family of mangoes using Artificial Intelligence. To achieve this goal, the study uses a deep learning algorithm that was trained on 1524 images of the fruit. The data used was divided into four classes: 'unripe', 'early-ripe', 'partially-ripe' and 'ideally-ripe'. In progression to this, the research correlates 'RRCO2' and the ripeness level of the Mango.

The prediction accuracy using 'VGG-16’ [8] on the training dataset was 99%, and the test data set was 96.2%. Near-infrared spectroscopy was used in [9] to analyze the quality of apples at different stages. Unfortunately, there are very limited literatures on fruit shelflife prediction.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
ISSN: 3068-272X www.ijdim.com Original Research Paper

This research is focused on building a real-time, self-learning model that considers changing information from observations made at the unit level of a fruit throughout every step of the supply chain. The research aims to assess how well a self-learning model predicts storage life and how the existing supply chain can be made more efficient. The accuracy of prediction is close to 98.15%. The paper [10] aims to predict the maturity and quality in terms of the shelf life of fruit. The fruit used was a Banana. The study used a total of 2100 images that were divided into 3 classes: ripe, unripe, and over-ripe, with each containing 700 images. Additionally, it used two sets of datasets.

Convolutional neural networks (CNN) and AlexNet [11] algorithms were used to achieve the goal, and the study concluded that CNN was a more suitable algorithm for the dataset used in the research, and its highest accuracy obtained was 99.36%. It can be concluded that various methods proposed in the above-mentioned research papers differ from those used in this study. This research involves estimating of shelf life of banana using object detection techniques, namely Faster RCNN and YOLOv5. It compares the performance of both the models on various grounds, while the above methods proposed by different research studies involve VGG-16, SqueezeNet ShuffleNet, MobileNetv2, CNN and AlexNet.

With increasing need for sustainability within the food supply chain, the quality control and food monitoring of agricultural commodities based non-destructive testing has gained in valuable interest [12,13,14,15].

3. PROPOSED SYSTEM

The proposed system focuses on leveraging time-series temperature data and deep learning models to accurately predict the shelf life of fresh produce during storage and transportation. Initially, the system begins with structured datasets containing temporal and temperature-related values.

These datasets are vital for training predictive models, where the primary goal is to estimate the lifespan of perishable goods.

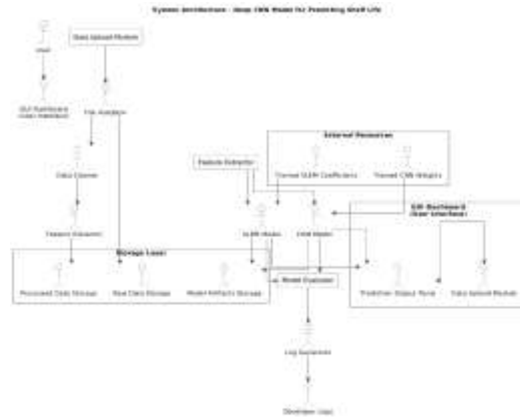


Fig. 2: Proposed block diagram

Once the data is collected, preprocessing is performed to clean and prepare it for modeling. This includes handling missing values, normalizing features, encoding categorical variables, and removing outliers. Ensuring high-quality data input is essential for building a robust model.

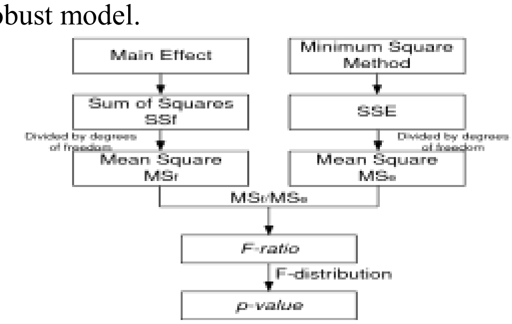


Fig. 3: Anova Step-Wise Diagram.

Following preprocessing, Analysis of Variance (ANOVA) is applied to statistically assess the impact of temperature variations on the lifespan of produce. ANOVA evaluates whether differences in mean shelf life across various temperature ranges are significant, thereby helping in feature selection. However, since ANOVA is limited to categorical variables and assumes data normality, it is mainly used here as a comparative baseline. To address the complex

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
ISSN: 3068-272X www.ijdim.com Original Research Paper

and nonlinear nature of real-world temperature data, a Convolutional Neural Network (CNN) model is proposed. CNNs are capable of capturing spatial and temporal patterns in sequential data, making them ideal for predicting dynamic changes in shelf life. The CNN processes input data through layers that include convolutional, pooling, and fully connected networks. These layers extract features, reduce dimensionality, and ultimately provide a prediction based on learned representations.

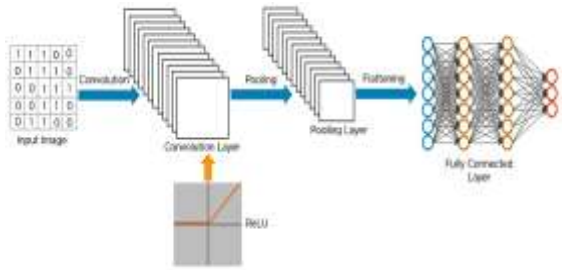


Fig. 4: CNN Architectural Diagram.

The CNN model's performance is evaluated against traditional methods such as ANOVA and regression-based algorithms. Evaluation metrics like mean squared error, accuracy, and R-squared values are used to demonstrate the model's superiority. Data is split into training, validation, and test sets, with stratified sampling applied to maintain balanced distributions. Preprocessing continues with scaling (using Min-Max or standardization), sequence creation for time-series learning, and, if necessary, synthetic augmentation to improve model generalization.

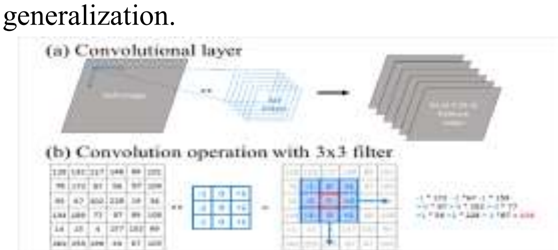


Fig. 5: Basic Convolution Operation.

ANOVA, as a statistical method, breaks down total variance into within-group and between-group variance. It uses the F-statistic and p-value to determine statistical significance between group means. While useful for identifying influential features, ANOVA's limitations include sensitivity to outliers and an inability to specify which groups differ without additional post-hoc analysis. It also requires assumptions of normality and equal variances, which often do not hold in real-world logistics datasets.

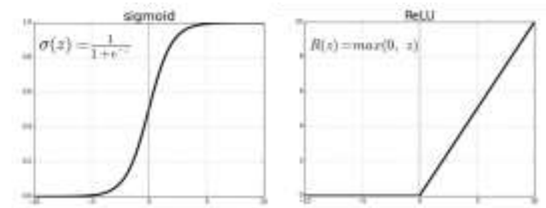


Fig. 6: Activation function used between the hidden layers. (a) Sigmoid, (b)ReLU

In contrast, CNNs offer a more adaptive and powerful modeling approach. They work by applying filters that move across the data to detect important patterns. These filters generate feature maps that are then passed through activation functions like ReLU to introduce non-linearity, enabling the network to learn complex dependencies. Pooling layers follow, reducing spatial dimensions while preserving critical information. This is particularly effective in minimizing computational load and overfitting. Fully connected layers at the end of the network combine all learned features, and the SoftMax function is used to output probabilistic class predictions in multi-class tasks. The SoftMax converts logits into a probability distribution, making interpretation straightforward and actionable.

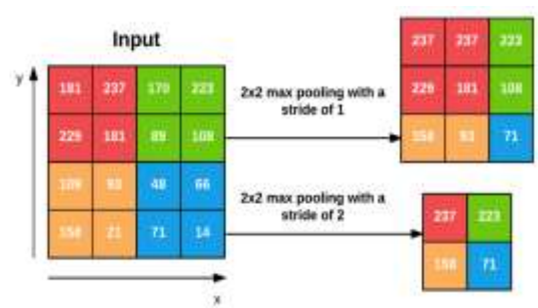


Fig. 7: Max pooling Layer

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
ISSN: 3068-272X www.ijdim.com Original Research Paper

CNNs come with multiple advantages that make them ideal for this application. They support hierarchical learning, automatically identifying low- and high-level features. They exhibit translation invariance, allowing consistent pattern recognition regardless of input position.

Their design incorporates parameter sharing, which reduces model complexity and training time. Sparse connectivity ensures that only the most relevant parts of the data influence predictions, making the network both efficient and scalable.

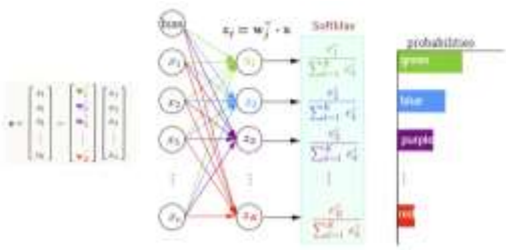


Fig. 8: Fully Connected Layer with SoftMax classifier

Local receptive fields allow the model to learn dependencies within small input regions, which is especially useful for identifying gradual changes in temperature over time. CNNs have consistently delivered top-tier performance across a wide range of real-world applications, and their integration into this shelf-life prediction system offers promising improvements in cold chain efficiency, reduced spoilage, and better-informed decision-making throughout the agricultural supply chain.

4. RESULTS AND DISCUSSION

The below figure 8 showcases the graphical user interface (GUI) designed for predicting the shelf life of fruits and vegetables. The interface features a user-friendly layout with input fields, buttons, and display areas tailored for entering data related to fruit and vegetable characteristics, such as type, ripeness, storage conditions, or other relevant parameters. The GUI include sections for uploading datasets, initiating predictions, and viewing results, possibly with visual elements like graphs or tables to present shelf-life predictions.

The design is intuitive, aimed at enabling users, such as farmers or researchers, to interact seamlessly with the prediction system without requiring extensive technical expertise.

Fig. 9: GUI of Predicting shelf life of fruits and vegetables

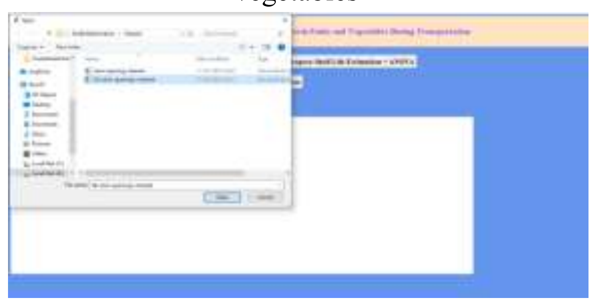
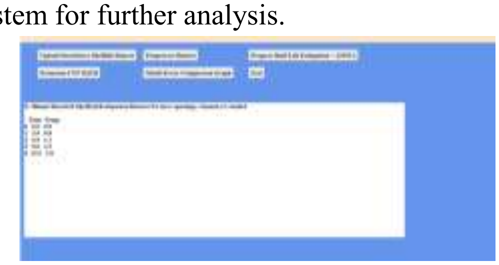


Fig. 10: Uploading the Dataset of fruits and vegetables.

The above figure 10 illustrates the process of uploading a dataset into the shelf-life prediction system. It depicts a specific section of the GUI where users can select and upload a file containing data about fruits and vegetables, such as a CSV or Excel file. The interface shows a "Browse" or "Upload" button, a file path display, and possibly a progress bar or confirmation message indicating the upload status. The figure emphasizes the ease of importing structured data, which include attributes like fruit type, harvest date, or environmental factors, into the system for further analysis.



International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
ISSN: 3068-272X www.ijdim.com Original Research Paper

Fig. 11: Uploaded Dataset in GUI interface.

The figure 11 displays the GUI interface after the dataset of fruits and vegetables has been successfully uploaded. It shows a tabular or structured view of the dataset within the interface, with columns representing attributes and rows corresponding to individual entries. The figure highlights how the GUI organizes and presents the uploaded data, making it accessible for users to review before proceeding with shelf-life predictions.

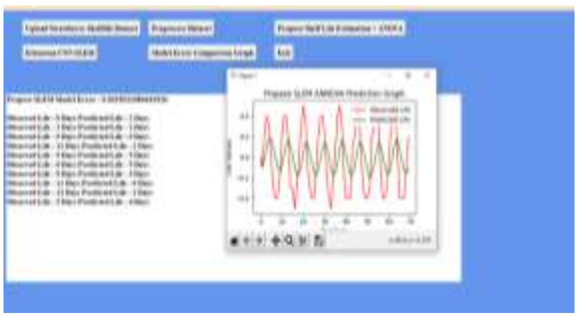


Fig. 12: Prediction of Shelf life using SLEM

The figure 12 shows the Propose Shelf-Life Estimation + ANOVA' button to train ANOVA and then predict future shelf life of fruits and vegetables. In above screen propose model got 30% error rate and in next lines can see Observed or original 'shelf life' and then can see predicted shelf life and can see close difference between original and predicted shelf life. In graph x-axis represents number of test data and y-axis represents shelf life where red line is for original shelf life and green line is for predicted shelf life. In above graph can see both lines are overlapping with some gap so we can say prediction is little accurate

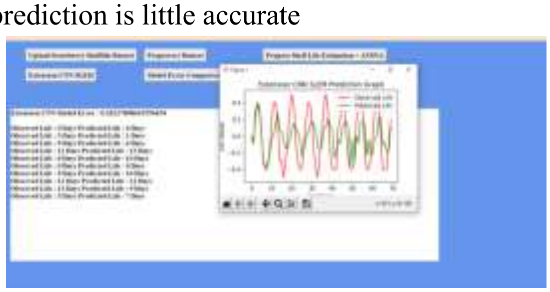


Fig. 13: Prediction of shelf life using Proposed Extension CNN

In above figure 13 it shows that the extension CNN model got 0.26% error which is lesser than propose algorithm and can see original and predicted shelf life and in graph also can see green and red line overlapping closely.

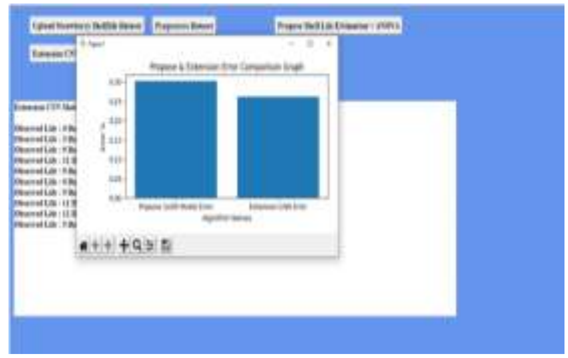


Fig. 14: Comparison graph of SLEM and Extension CNN.

In above figure 14 shows the can see comparison between propose and extension algorithm where x-axis represents algorithm names and y-axis represents model error and, in both algorithms, extension got less error compare to propose ANOVA SLEM algorithm. Similarly, you can upload and test other algorithms.

5. CONCLUSION

Efficient management of fresh produce is a cornerstone of reducing food wastage and ensuring food security, particularly in a country like India, where agricultural production is vast but post-harvest losses remain high. Traditional systems for predicting the shelf life of fruits and vegetables have relied heavily on static guidelines, manual inspections, and historical data—methods that lack precision and adaptability. These approaches often result in significant spoilage and economic losses, underscoring the need for a more innovative solution. The introduction of deep learning-based models represents a transformative step in addressing these challenges. By leveraging Convolutional Neural Networks (CNNs) trained on temperature simulation data, shelf life can now be predicted with high accuracy in real time. This advancement enables dynamic monitoring and adjustment of storage and transportation conditions, thereby minimizing spoilage and improving logistics efficiency. Moreover, these models empower stakeholders to optimize distribution routes, reduce operational costs, and ensure that fresher produce reaches consumers. The adoption of AI in shelf-life prediction offers multiple benefits, including actionable insights such as alerts for optimal consumption times and recommendations for adjusting storage parameters. Real-time data integration across the supply chain also fosters improved collaboration among farmers, distributors, and retailers. By reducing reliance on subjective assessments and outdated guidelines, this data-driven approach ensures a proactive and intelligent strategy for managing perishable goods.

REFERENCES

[1] Omid, Mahmoud & Soltani Firouz, Mahmoud & Nouri-Ahmadabadi, Hosein & Mohtasebi, Seyed. (2017). Classification of peeled pistachio kernels using computer vision and color features. Journal of the Science of Food and Agriculture. 10. 259–265. 10.1016/j.eaef.2017.04.002.

[2] Bhole, V., & Kumar, A. (2021). A Transfer Learning-based Approach to Predict the Shelf-life f fruit. Inteligencia Artificial, 24(67), 102– 120. https://doi.org/10.4114/intartif.vol24iss67pp102-120. 5

[3] Ramani, M & Tarpara, Vrajlal & Swaminathan, B. & Manasi, P & Pokiya, N. (2019). COST OF CULTIVATION AND PROFITABILITY OF KESAR MANGO CULTIVATION IN SAURASHTRA REGION OF GUJARAT, INDIA.

[4] Iandola, Forrest N., et al. "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size." arXiv preprint arXiv:1602.07360 (2016).

[5] Shahi TB, Sitaula C, Neupane A, Guo W (2022) Fruit classification using attention-based MobileNetV2 for industrial applications. PLoS ONE 17(2): e0264586. https://doi.org/10.1371/journal.pone.0264586

[6] Dutta, J., Deshpande, P. & Rai, B. AI-based soft-sensor for shelf-life prediction of 'Kesar' mango. SN Appl. Sci. 3, 657 (2021). https://doi.org/10.1007/s42452-021-04657-7 5

[7] Bhande, S.D. & Ravindra, M.R. & Goswami, T.K. (2008). Respiration rate of banana fruit under aerobic conditions at different storage temperatures. Journal of Food Engineering. 87. 116-123. 10.1016/j.jfoodeng.2007.11.019.

[8] Tammina, Srikanth. (2019). Transfer Learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images. International Journal of Scientific and Research Publications (IJSRP). 9. p9420. 10.29322/IJSRP.9.10.2019. p9420.

[9] J.C. Fan, G.M. Zhou, "A Near infrared spectroscopy qualitative analysis of apple shelf life", Food and Nutrition in China, 17:47-49, 2011. doi: https://doi.org/10.3390/molecules200813603.

[10] Aherwadi, N.; Mittal, U.; Singla, J.; Jhanjhi, N.Z.; Yassine, A.; Hossain, M.S. Prediction of Fruit Maturity, Quality, and Its Life Using Deep Learning Algorithms. Electronics 2022, 11, 4100. https://doi.org/10.3390/electronics11244100 1

[11] Abasi, S.; Minaei, S.; Jamshidi, B.; Fathi, D. Dedicated non-destructive devices for food quality measurement: A review. *Trends Food Sci. Technol.* 2018, *78*, 197–205.

[12] Hussain, A.; Pu, H.; Sun, D.W. Innovative nondestructive imaging techniques for ripening and maturity of fruits—A review of recent applications. *Trends Food Sci. Technol.* 2018, *72*, 144–152.

[13] Mohd Ali, M.; Hashim, N.; Bejo, S.K.; Shamsudin, R. Rapid and nondestructive techniques for internal and external quality evaluation of watermelons: A review. *Sci. Hortic.* 2017, *225*, 689–699.

[14] Arendse, E.; Fawole, O.A.; Magwaza, L.S.; Opara, U.L. Non-destructive prediction of internal and external quality attributes of fruit with thick rind: A review. *J. Food Eng.* 2018, *217*, 11–23.

[15] Paul, V.; Pandey, R.; Srivastava, G.C. The fading distinctions between classical patterns of ripening in climacteric and non-climacteric fruit and the ubiquity of ethylene-An overview. *J. Food Sci. Technol.* 2012, *49*, 1–21. [Green Version]