REDVET - Revista electrónica de Veterinaria - ISSN 1695-7504
Vol 25, No. 1 (2024)
http://www.veterinaria.org
Article received- Revised- Accepted-

Optimizing Agricultural Product Quality With Machine Learning-Enabled Grading Systems

Swapnil Desai[1*], Dr. Manuj Joshi[2], Dr. Pradip Mane

[1*]Research Scholar, PAHER University, Udaipur, India. Email: swapnildesai2022@gmail.com
[2]Professor, PAHER University, Udaipur, India.Email: manujjoshi@gmail.com
[3]Associate Professor, VPPCOE&VA Mumbai, India. Email: pradip.mane@pvppcoe.ac.in

***Abstract*—** Coherence Shock Filtering (CSF), which is used to improve the sharpness and decrease blurriness of fruit photos, is the first step in the suggested approach. The pictures are then subjected to a Discrete Wavelet Transform (DWT) in order to identify key characteristics for additional categorization. The Marine Predators Algorithm (MPA) is used for optimal feature selection in order to guarantee that only the most pertinent features are taken into account. The Water Wheel Plant Algorithm (WWPA) handles the classification stage, classifying the fruit photos as either healthy or unhealthy. The model outperformed previous approaches with remarkable accuracy rates of 99.9% and 99.98% on two well-known datasets: Fruits 360 and Fresh and Rotten Fruits.

Keywords—Fresh and rotten fruits , Grading , Agricultural products , Quality

I. INTRODUCTION

Agriculture is seen as a crucial component of the global economy, as well as meeting one of humanity's most fundamental needs, namely food. In the majority of countries, it is considered the primary source of employment. Many nations, such as India, continue to use conventional farming methods; farmers are hesitant to employ new agricultural technology due to a lack of expertise, high costs, or a lack of awareness of the benefits of such technologies. Lack of understanding of soil types, yields, crops, weather, poor pesticide application, irrigation issues, incorrect harvesting, and a lack of market trend information led to farmer losses or increased costs. Lack of information at each level of agriculture creates new difficulties or exacerbates existing problems, increasing the expense of farming. Population growth adds pressure on the agriculture industry on a daily basis. Overall losses in agricultural systems, from crop selection to product sales, are quite substantial. According to the classic proverb "Information is Power," maintaining track of information on crops, the environment, and the market may help farmers make better decisions and solve agricultural challenges. Block chain, IoT, machine learning, deep learning, cloud computing, and edge computing are all technologies that may be used to collect and analyse data. Applications of computer vision, machine learning, and IoT will assist to increase productivity, enhance quality, and ultimately increase the profitability of the farmers and associated domains.

Farmers often follow the following procedures when completing agricultural operations.
Step 1: Choose a Crop
Step 2: Land Preparation.
Step 3: Seed Sowing
Step 4: Irrigation and fertilization.
Step 5: Crop Maintenance (application of pesticides, crop trimming, etc.)
Step 6: Harvesting.
Step 7: Post-Harvest activities

The algorithm categorizes agricultural tasks into main sub-areas. Figure 1 illustrates the four sub-domains of agricultural chores.
Recent improvements in digitization technology in the food industry have resulted in a major global revolution. Artificial intelligence (AI) has played an important part in our daily lives by developing extensive domain technology that mimics a human brain. This technology utilizes clever software and gadgets to mimic the human brain's decision-making and problem-solving processes. Intelligent gadgets use training datasets to create desired results, analogous to the human brain. The advancement of digital technology has created the potential for AI-driven data analytics, resulting in decision-making and automated data collecting. AI helps humans with probabilistic reasoning and predictive modeling. The investigation of these strategies revealed a simple strategy that may be understood as the enhancement of human cognitive capacities. AI is increasingly being utilized to evaluate the quality of food and agricultural goods in response to global food demand and technological advancements. AI is a potential technology for evaluating food quality using a computer system. In this view, AI acts as a strong and wide-ranging tool, paired with new technology such as cloud computing.
Food quality inspection involves painstaking analysis and sample destruction. Monitoring food quality and shelf-life is one of the top issues. Practically, the measurement of food quality demands a quick, efficient, and precise analysis. Data analysis from the measurement of dietary qualities is particularly significant for the A high number of datasets may contain information that is unnecessary or redundant. As a result of turning digital, the usage of AI, an influential analytic

tool, was discovered ideal for quality. Inspections of different food and agricultural items. The core of AI consists of machines.
Machine learning algorithms, such as partial least squares (PLS), support vector machine (SVM), artificial neural network (ANN), k-nearest neighbor (kNN), and random forest, are commonly used for food quality inspection and prediction. Machine learning algorithms outperformed traditional methods for categorizing fruits based on maturation stages. Deep learning has attracted attention for evaluating food quality due to its capacity to represent data. Deep learning has been used in quality detection systems for several food products, including apples, butter, tomatoes, grapes, olive oil, and beef.

A. Key Concepts of AI

AI has the potential to revolutionize food demand by allowing for quick quality screening of food and agricultural products. The potential for digital change in food quality monitoring can showcase the concepts and advancements of AI. This section introduces the fundamentals of AI, including expert systems, ANN, and fuzzy logic. These technologies may be used to decrease human interaction and effort.

B. Expert System

It has been emphasized that the capacity to solve complicated issues through reasoning and knowledge representation. Four types of expert systems: rule-based, frame-based, semantic network, and logical album, based on knowledge representations. Expert systems typically include knowledge acquisition, knowledge base, HMI, dynamic database, inference engine, and interpreter. The expert system's problem-solving process simulates expert thinking through knowledge information. Previously an expert system for ordinary devices that improved a limited number of variables based on forecast performance has been developed.

C. ANN

Artificial neural networks (ANNs) are commonly employed in AI to detect food quality. An artificial neural network (ANN) is a mathematical model with linear or non-linear processing characteristics called nodes. In theory, the electrical signal travels via neurons using axons in an interconnected neural network in which the signal flows across synapses at each node's tip. The Working premise of ANN is comparable to the human brain, in that it tells the system to work appropriately to an in-built job as an alternative to a traditional computational assignment. The fundamentals architecture of ANN has three primary layers: the input layer, the hidden layer, and output layer. The input layer collects data from the architecture, which is subsequently processed by the hidden layer. The acquired information is transferred to the output layer, which connects the nodes to generate the final output. ANN layers offer benefits such as predicting parallel thinking and efficient neural network training. ANN refers to a learning algorithm, neuron model, and architecture that describe the pattern interaction between neurons and layers.

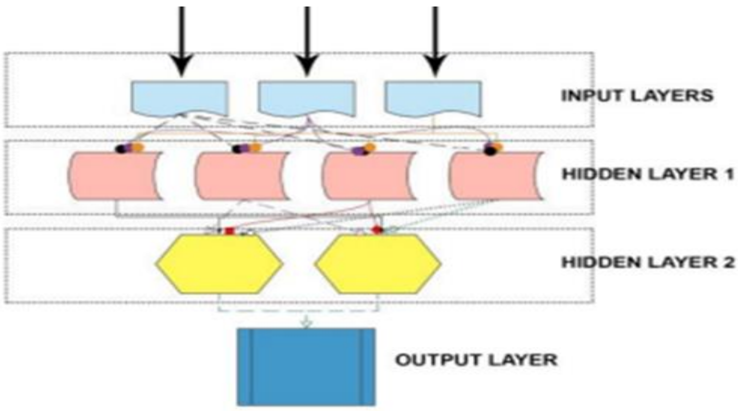


Fig.1. Artificial neural network layers

D. Fuzzy Logic

Fuzzy logic is a type of AI that mimics human decision-making and reasoning through fuzzy inference, fuzzification, rule base, and defuzzification . Fuzzy logic works by deciphering interfering knowledge into fuzzy rules (Figure 2). Fuzzy processing converts input signals into fuzzy inputs, leading to imprecise conclusions. Fuzzy interference is recovered by creating input degrees using fuzzy rules for synthesis control. After defuzzing the fuzzy conclusions, the system generates particular output data. Fuzzy logic uses 'if-then' rule statements to represent the relationship between inputs and outputs after defuzzification. Common defuzzification methods include central mean, maximal criterion, and center of gravity.

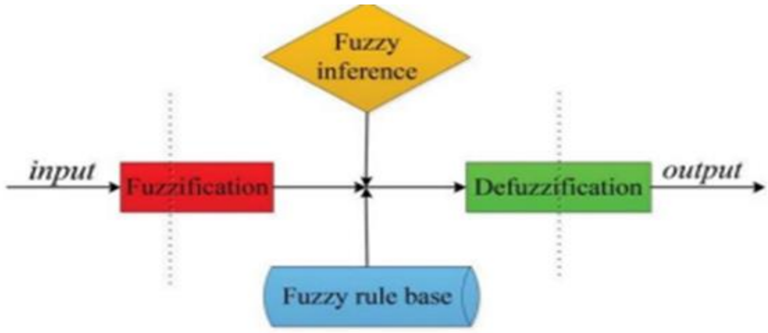


Fig.2. Schematic Diagram of Fuzzy

What is Fruit Grading?

Fruit grading is a crucial process in the agricultural supply chain where fruits are assessed for their quality and market value. This involves sorting fruits based on various parameters such as size, color, shape, texture, ripeness, and the presence of any external defects such as bruises, spots, or blemishes. Proper fruit grading ensures that consumers receive high-quality products, while producers and retailers can maximize their profits by determining the price and marketability of their produce based on consistent quality standards.

Key Factors in Fruit Grading:

1. Size: Larger, well-formed fruits are often considered premium in terms of quality.
2. Color: Uniformity and vibrancy of color indicate ripeness and freshness. For example, a uniformly red apple is generally preferred over one with uneven coloration.
3. Shape: Deviations from the typical shape of a fruit can indicate poor development or potential internal defects.
4. External Defects: Visible defects like bruises, punctures, or decay are used to determine fruit quality. Fruits with minimal or no visible damage are graded higher.
5. Firmness and Texture: These attributes can indicate the ripeness and freshness of the fruit, affecting its shelf life.

Traditionally, fruit grading has been performed manually by experienced workers, who visually inspect each piece of fruit. However, this method is not only labor-intensive but also subject to inconsistencies due to human error. As a result, the demand for automated grading systems has grown, leading to the integration of machine learning and image processing technologies in the fruit grading process.

Automating Fruit Grading with Algorithms

Technological advancements have become a pivotal force in reshaping the agricultural sector, particularly in fruit cultivation. Over recent decades, these innovations have driven steady growth in both crop yields and the accuracy of global fruit quality assessments. As a result, increased productivity and the availability of data have heightened competition among the top fruit producers worldwide [1][2]. However, one of the ongoing challenges in this field is ensuring accurate and efficient sorting of agricultural products. The quality of these products plays a crucial role in determining their market value and overall customer satisfaction [3].

To address this issue, the agricultural sector requires intelligent detection systems that can boost productivity and maintain competitiveness [4]. Previous research has focused on developing automated methods for fruit grading, aiming to meet the industry's growing demands. With the global population projected to reach 9.7 billion by 2050, the agricultural industry faces the dual challenge of increasing production while managing uncertainties related to climate change, limited resources, and shifting consumer preferences. Given these factors, efficient grading and quality control of agricultural products are essential to ensure sustainability [5][6][7].

Technological innovations have spurred significant changes within the global agricultural industry, leading to the exploration of advanced, data-driven solutions. One promising approach is the incorporation of Machine Learning (ML) techniques into agricultural processes. These methods range from analyzing physical and chemical attributes, such as firmness and soluble solid content, to non-invasive image processing techniques for evaluating color, texture, and fruit maturity. It's important to recognize that the performance of ML models in these applications heavily depends on the availability of large, high-quality datasets for training [8].

Advantages of using Machine learning to Fruit grading

Ensuring product quality is a vital aspect of the agricultural sector, particularly in delivering safe and high-quality goods to consumers. Agricultural product quality is influenced by a broad range of factors including environmental conditions (e.g., soil quality, temperature, and precipitation), farming techniques (e.g., irrigation, pest control, and fertilizer usage), and post-harvest processing such as storage and transportation. Key indicators of quality include attributes like freshness,

taste, nutritional value, and safety, which are essential not only for consumer satisfaction but also for meeting regulatory standards.
Traditionally, quality control in agriculture has involved manual inspection, where workers visually assess products and use sensory evaluations like taste and smell. While this method has been effective for centuries, it is time-consuming and inherently subjective, often leading to inconsistent results and human error. Additionally, with increasing global demand and larger production volumes, manual inspection is becoming less practical.
The introduction of machine learning (ML) technologies has revolutionized the agricultural quality control process. Machine learning algorithms offer the potential for more accurate, efficient, and scalable solutions to grading and quality assessments. By analyzing images, chemical compositions, and other data points, ML models can quickly and consistently evaluate factors such as color, size, texture, and ripeness, all of which are critical for determining the quality of agricultural products.
One advantage of using machine learning in agriculture is the ability to process vast amounts of data in real time, allowing for early detection of issues such as spoilage or contamination. Moreover, ML systems can learn and adapt over time, improving their accuracy with every dataset they process. These technologies can also integrate with other systems like IoT sensors, drones, and satellite imagery to provide a comprehensive view of crop conditions and product quality, leading to more informed decision-making on the part of farmers and producers.

As machine learning continues to evolve, it promises to address the limitations of traditional quality control methods in agriculture. Automated systems not only reduce human error but also offer faster, more reliable grading processes. This ultimately results in higher-quality products reaching consumers, increased operational efficiency, and better compliance with both consumer expectations and regulatory requirements.

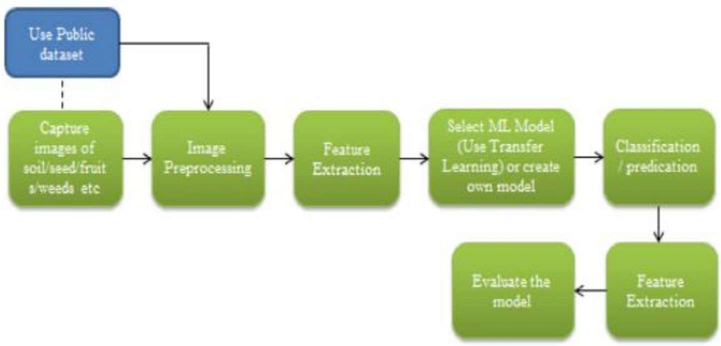


Fig.3. Machine Learning Used in Literature

II. LITERATURE REVIEW

The grading of agricultural products is essential for maintaining quality and ensuring fair pricing in the agricultural sector. Traditionally, grading has been conducted manually, which can lead to inefficiencies, human errors, and variability in quality assessments. Recent advancements in machine learning (ML) and artificial intelligence (AI) have presented opportunities to automate and enhance grading processes. By utilizing intelligent detection systems powered by ML, farmers and industries can improve the quality and consistency of agricultural products, optimize labor, and increase market competitiveness. CNNs have been widely adopted in grading fruits and vegetables. Zhang et al. (2020) demonstrated that a CNN-based approach could classify tomatoes into different grades with a high accuracy rate, improving upon traditional methods [1].

III. Techniques and Approaches

- **Computer Vision and Image Processing**: One of the foundational approaches in intelligent grading is the use of computer vision combined with ML algorithms. High-resolution images of agricultural products are processed, and features such as color, shape, and size are extracted for classification. Zhou et al. (2018) implemented a machine-learning framework that graded apples by analyzing visual defects using a support vector machine (SVM) algorithm. They reported an accuracy of over 90%, demonstrating that ML can outperform manual inspection [2].

Deep Learning Models: Deep learning, particularly CNNs, has revolutionized intelligent grading. These models are trained on large datasets of labeled images to detect features like ripeness, bruises, and diseases. For instance, Picon et al. (2019) developed a CNN-based system for assessing the ripeness of bananas. The system accurately predicted ripeness stages, enabling optimized harvest timing [3].

- **Multispectral and Hyperspectral Imaging**: Advanced imaging techniques such as hyperspectral imaging, combined with ML, can capture data across different spectral bands, providing insights into the internal and external quality of products. Using these spectral images, ML algorithms can assess parameters like sugar content or moisture levels.

REDVET - Revista electrónica de Veterinaria - ISSN 1695-7504
Vol 25, No. 1 (2024)
http://www.veterinaria.org
Article received- Revised- Accepted-

ElMasry et al. (2021) integrated a hyperspectral imaging system with machine learning models to evaluate the sugar content in melons, reporting high precision and consistency compared to conventional methods [4].

- **Pest and Disease Detection**: Intelligent grading systems also include pest and disease detection, a critical factor in determining the quality of agricultural products. Kamilaris and Prenafeta-Boldú (2018) utilized deep learning models to detect diseases in crops from images. Their approach significantly reduced the time needed for disease detection and improved the accuracy of grading systems [5].

IV. Proposed Method

The initial step in the image analysis process involves pre-processing the input data. This stage employs techniques that enhance the visibility of crucial edges and reduce blur in various regions of the image, leveraging the Contrast Sensitivity Function (CSF). The refined data is then subjected to a Discrete Wavelet Transform (DWT) to extract relevant features that facilitate detection. Subsequently, the most informative features are selected using the Marine Predator Algorithm (MPA). The overall architecture of the SGXGBoost method is illustrated in Figure 1. Ultimately, the proposed SGXGBoost approach, as described in WWPA, categorizes fruits such as apples, oranges, bananas, and avocados as either healthy or diseased, and assigns a quality ranking accordingly.

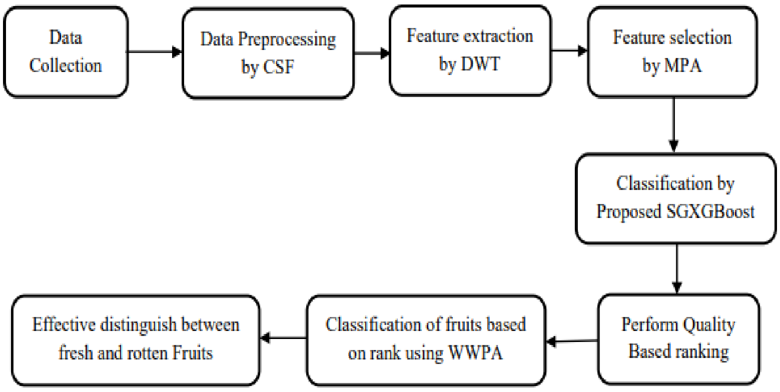


Fig 4 Proposed SGXGBoost Flow

A. Extracting Features

Discrete Wavelet Transform

This phase includes the extraction of features that will be further used for the detection [14]. Following pre-processing, the data is directed to the feature extraction phase based on the Discrete Wavelet Transform (DWT) to obtain the pertinent characteristics for detection. The DWT is a signal processing technique that facilitates the analysis and extraction of valuable information by decomposing a signal or dataset into distinct frequency components. This process involves dividing the data into multiple scales or levels, each representing a unique resolution or level of detail. By capturing both high-frequency and low-frequency components, the DWT enables a more comprehensive representation of the data. In this study, the desirable features of the pre-processed image are extracted using the low-high subband.

The mathematical formulation of the DWT method is presented in Equation (1):

$FWT(\varphi) = \sum \beta * \theta$ ………………………………… (1)

where φ represents the sampling point of the signal, θ represents the low-high subband wavelet function, and $FWT(\varphi)$ represents the feature extraction variable through the signaling function.

By Marine Predatorsal Algorithm (MPA)

Following feature extraction, the Marine Predator Algorithm (MPA) is employed to select the most informative features [15]. The MPA is a metaheuristic algorithm inspired by natural predatory behavior, which efficiently explores the search space to identify optimal solutions. Initially, the algorithm surveys the search space to detect areas with potential solutions and then refines its search to find the most suitable answer. The MPA initiates by utilizing information from the exploration position to generate the first set of solutions.

This process is mathematically formulated as:

$\Omega mn = \Lambda n + \rho * (\Omega n - \Lambda n), n = 1,2,...,t, m = 1,2,...,D$ …..(4)

where Ω mn represents the initial set of predator solutions, Ωn and Λn denote the higher and lower regions in the search position at dimension n, and $\rho \in [0,1]$ signifies a random number within the boundary. This equation is used to update the position of the predator in the search space, where the random number scales the difference between the higher and lower regions ρ. This allows the algorithm to explore the search space efficiently and avoid getting stuck in local optima.

REDVET - Revista electrónica de Veterinaria - ISSN 1695-7504
Vol 25, No. 1 (2024)
http://www.veterinaria.org
Article received- Revised- Accepted-

The evaluation of the fitness function is minimized to select the relevant subset of features and reduce the classification error using the following equation:

fitness(Ω) = (1 - γ)E + γ(C / |Ω|) ………………...(5)

where E represents the classification error obtained by the feature selection set Ω, C represents the reduced dimension of features, and γ represents the balance factor, which lies in the range of [0,1]. The balance factor controls the consequence of the classification error and feature set reduction on the total fitness. The fitness function is a weighted sum of the classification error and the feature set reduction, where the weight γ determines the relative importance of each term. By minimizing the fitness function, the MPA selects the feature subset that balances the trade-off between classification accuracy and feature dimensionality.

The MPA's ability to efficiently explore the search space and converge to optimal solutions makes it an effective feature selection technique. The detailed procedure of the MPA algorithm is outlined in preceding sections.
Additionally, the MPA's application in feature selection has been shown to improve the performance of various machine learning models, including the proposed SGXGBoost approach. By selecting the most informative features, the MPA helps to reduce the dimensionality of the data, improve model interpretability, and enhance the overall classification accuracy.

Classification of fruits by proposed stacked generalization based extreme gradient boosting tree
The proposed model employs SGXGBoost for classification tasks, using optimal features as inputs [16][17]. It performs binary classification, distinguishing between two categories: healthy and unhealthy. SGXGBoost's regularization technique is particularly effective at preventing over fitting, which enhances the model's efficiency and robustness compared to other gradient-boosting methods.
The model also incorporates stacked generalization, utilizing the SGXGBoost classifier to work with prediction probabilities. This approach helps reduce generalization errors by addressing biases present in individual sub-models.

In simpler terms, the model leverages SGXGBoost to categorize inputs into healthy or unhealthy, focusing on avoiding overfitting and boosting model performance. Stacked generalization further improves accuracy by accounting for the biases of different sub-models.
Consider an ensemble of P independent features, which signifies U U UP , ... 1 2 ,with D - dimensional vectors. Where, [0,1] Um,n ∈ .Thus, the ensemble decision applied for the input images through Eqn (4).

$$\sum_{m=1}^{J} \square \sum_{m=1}^{\bar{J}} U_{1,P} = max_{m=1}^{g} \sum_{m=1}^{j} U_{m,n}$$

where, g represents the multi class weight coefficient. The coefficients of importance are signified as q m p m , = 1,2,.... ,The class label is attained through Eqn (5).

$$\sum_{m=1}^{\bar{J}} q_m U_{1,p} = max_{m=1}^{g} \sum_{m=1}^{J} q_m U_{m,n}$$

The outputs are aggregated through maximum weighted majority voting to enhance the overall routine of the classifier. The regularization term is utilized to derive the objective function by
Eqn (6). Objective(κ) = Loss(κ) + Π(κ) …...(6)
Where, Loss (κ) represents the loss function of the classifier, Π(κ)represents the regularization function to avoid over fitting

Steps of Marine Predatorsal Algorithm

Input: Initialize the population feature subset
The Marine Predators Algorithm (MPA) is a meta-heuristic optimization technique inspired by the foraging strategies of marine organisms. It is used for feature selection in various applications, including fruit classification. Here are the general steps of the MPA for feature selection in fruits:

- **Initialization:** Start by defining the initial population of predators. Each predator represents a potential solution to the feature selection problem. The population size, number of features, and other parameters are set based on the specific problem and dataset.
- **Foraging Strategy:** Each predator in the population explores the feature space to find the optimal subset of features. This involves evaluating different combinations of features to determine which subset provides the best classification accuracy or other relevant metrics.

- **Competition and Cooperation:** Predators interact with each other through competition and cooperation. The algorithm models these interactions to mimic the natural behaviors of marine predators. This interaction helps in refining the search for better solutions.
- **Updating Predators**: Based on the interactions and evaluations, the positions of the predators are updated. This involves moving the predators towards better positions in the feature space, guided by the objective of maximizing classification accuracy or minimizing error.
- **Termination Criteria:** The algorithm continues until a predefined stopping criterion is met, such as reaching a maximum number of iterations or achieving a satisfactory level of accuracy.
- **Feature Selection:** Once the algorithm converges, the final positions of the predators represent the optimal subset of features. These features are then selected for use in the classification model.
- **Model Training and Evaluation**: The selected features are used to train a classification model, and the model's performance is evaluated on a separate validation set to ensure the effectiveness of the feature selection process.

V. Result and Discussion

The complete experiment has been performed through Python, Intel® Core i7 CPU and 16 GB memory.
The experimental outcomes were then compared with existing methods to validate the performance of the model.
Two datasets were utilized to evaluate the efficiency of the model: Dataset 1 included images of fresh and rotting apples, oranges, and bananas, while Dataset 2 contained images of fresh and rotten avocados. Both datasets are publicly available on the Kaggle platform.
The SGXGBoost model successfully classified the fruit images into healthy and unhealthy categories, demonstrating higher accuracy and robustness compared to traditional methods. Fig. 2(a-f) showcases examples of fruit classification for multiple fruit types in a single portrait, highlighting the effectiveness of the SGXGBoost method in identifying different classes of fruits. The results confirm that the model's regularization strategy effectively prevents overfitting, contributing to improved overall performance.

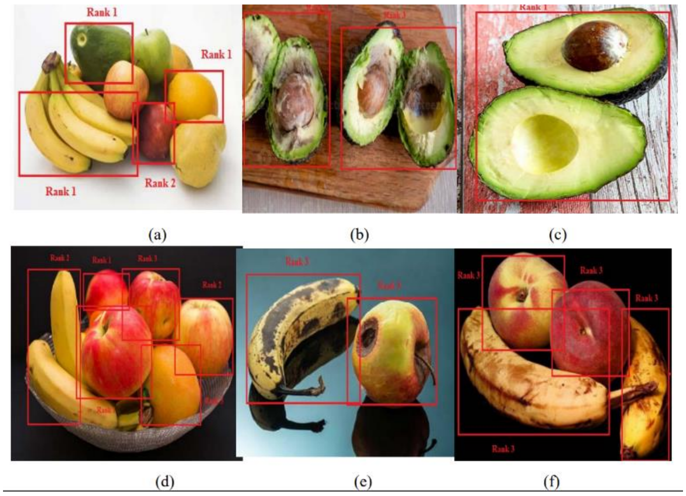


Fig.6. Classification results of fresh and rotten fruits based on ranking

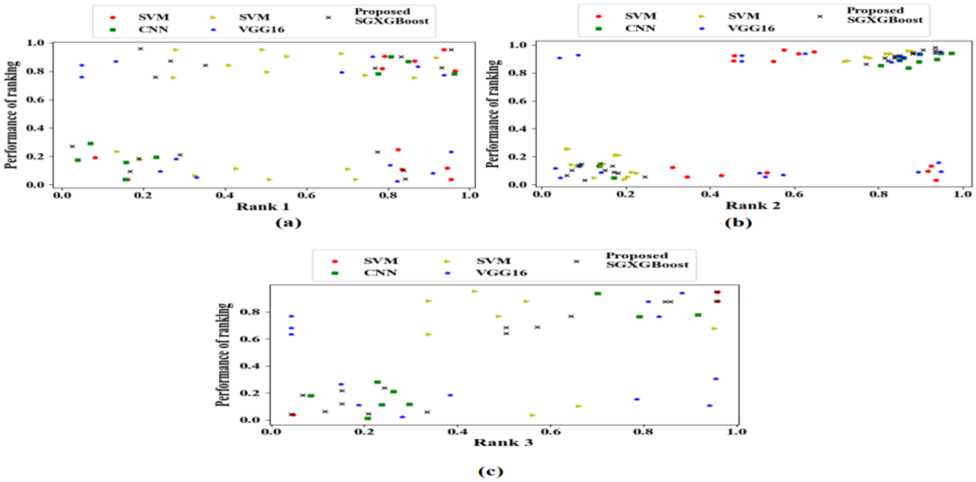
A. Dataset Description

As shown in Fig. 6(a-f), the proposed SGXGBoost model effectively distinguishes between fresh and rotting fruits across various conditions. The model's performance was also tested with multiple objects within the same image, demonstrating its robustness and reliability. Accurately assessing fruit freshness is crucial in preventing foodborne illnesses and minimizing related issues, which highlights the significance of this approach in agricultural and food safety applications.

B. Performance assessment of proposed SGXGBoost Model

Fig 4 illustrates the impact of the SGXGBoost model on ranking different fruit categories, including healthy, diseased, ripe, unripe, and fruit shape. The ranking process, which assigns fruits to categories based on their condition, was shown to be highly accurate.
Additionally, Fig 3(a-c) display the relationships between various fruit classes according to ranks 1, 2, and 3, respectively. The graphical results reveal that the SGXGBoost model consistently outperforms traditional methods in ranking performance. This improved accuracy in classification and ranking reinforces the model's potential for application in real-world scenarios, such as automated fruit sorting systems and quality control in the food industry.

REDVET - Revista electrónica de Veterinaria - ISSN 1695-7504
Vol 25, No. 1 (2024)
http://www.veterinaria.org
Article received- Revised- Accepted-



VI Conclusion
In conclusion, the integration of machine learning techniques into the agricultural sector offers a powerful and innovative approach to enhancing the quality of agricultural products. By processing large datasets, machine learning algorithms can identify patterns and trends that are not easily detectable by human analysis, enabling more informed decision-making. This research introduced an SGXGBoost model for the detection and classification of fruits based on their quality, categorizing them as either healthy or diseased. The SGXGBoost model's ability to accurately classify fruits based on their condition plays a significant role in improving overall quality control within the agricultural sector. Utilizing the WWPA algorithm, the model achieves high classification accuracy.

References
[1] Rosenzweig, C.; Karoly, D.; Vicarelli, M.; Neofotis, P.; Wu, Q.; Casassa, G.; Menzel, A.; Root, T.L.; Estrella, N.; Seguin, B.; et al. Attributing physical and biological impacts to anthropogenic climate change. Nature 2008, 453, 353–357. [Google Scholar] [CrossRef] [PubMed]J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[2]] Alanazi, H.O.; Abdullah, A.H.; Qureshi, K.N. A critical review for developing accurate and dynamic predictive models using machine learning methods in medicine and health care. J. Med. Syst. 2017, 41, 69. [Google Scholar] [CrossRef] [PubMed]

[3] Atzori, L. The internet of things: A survey. Comput. Netw. 2010, 54, 2787–2805. [Google Scholar] [CrossRef]

[4] Nath, R.K.; Thapliyal, H.; Caban-Holt, A.; Mohanty, S.P. Machine Learning based Solutions for Real-Time Stress Monitoring. IEEE Consum. Electron. Mag. 2020, 9, 34–41. [Google Scholar] [CrossRef]

[5] Lin, S.; Zhang, H.; Gao, Y.; Du, M.; Vai, M. The Effects of Muscle Stress on Signal Transmission in the Intra-Body Communication. In Proceedings of the 2016 IEEE International Conference on Consumer Electronics-China (ICCE-China), Guangzhou, China, 19–21 December 2016; pp. 1–3. [Google Scholar]

[6] Magaa, V.C.; Muoz-Organero, M. Reducing Stress on Habitual Journeys. In Proceedings of the 2015 IEEE 5th International Conference on Consumer Electronics - Berlin (ICCE-Berlin), Berlin, Germany, 6–9 September 2015; pp. 153–157. [Google Scholar]

[7] Ciabattoni, L.; Ferracuti, F.; Longhi, S.; Pepa, L.; Romeo, L.; Verdini, F. Real-Time Mental Stress Detection based on Smartwatch. In Proceedings of the 2017 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 8–10 January 2017; pp. 110–111. [Google Scholar]

[8]]Lawanot, W.; Inoue, M.; Yokemura, T.; Mongkolnam, P.; Nukoolkit, C. Daily Stress and Mood Recognition System Using Deep Learning and Fuzzy Clustering for Promoting Better Well-Being. In Proceedings of the 2019 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 11–13 January 2019; pp. 1–6. [Google Scholar]

[9] Nath, R.K.; Thapliyal, H.; Caban-Holt, A. Validating Physiological Stress Detection Model Using Cortisol as Stress Bio Marker. In Proceedings of the 2020 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 4–6 January 2020; pp. 1–5. [Google Scholar

[10] Lee, J.-M.; Byun, W.; Keill, A.; Dinkel, D.; Seo, Y. Comparison of Wearable Trackers Ability to Estimate Sleep.

[11] Sannholm, F.; Paalasmaa, J.; Leppakorpi, L. System for Determining the Quality of Sleep. US Patent 20 160 213 309A1, 31 December 2015. [Google Scholar]

[12] Bone, D.; Lee, C.; Chaspari, T.; Gibson, J.; Narayanan, S. Signal processing and machine learning for mental health research and clinical applications. IEEE Signal Process. Mag. 2017, 34, 196–195. [Google Scholar] [CrossRef]

[13] Osman, H.A.; Dong, H.; Saddik, A.E. Ubiquitous Biofeedback Serious Game for Stress Management. IEEE Access 2016, 4, 1274–1286. [Google Scholar] [CrossRef]

[14] Sano, A.; Picard, R.W. Stress Recognition Using Wearable Sensors and Mobile Phones. In Proceedings of the 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, Geneva, Switzerland, 2–5 September 2013; pp. 671–676. [Google Scholar]
[15] El-Samahy, E.; Mahfouf, M.; Torres-Salomao, L.A.; Anzurez-Marin, J. A New Computer Control System for Mental Stress Management using Fuzzy Logic. In Proceedings of the 2015 IEEE International Conference on Evolving and Adaptive Intelligent Systems (EAIS), Douai, France, 1–3 December 2015; pp. 1–7. [Google Scholar]
[16] Wijsman, J.; Grundlehner, B.; Liu, H.; Penders, J.; Hermens, H. Wearable Physiological Sensors Reflect Mental Stress State in Office-Like Situations. In Proceedings of the 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, Geneva, Switzerland, 2–5 September 2013; pp. 600–605. [Google Scholar]
[17] Choi, J.; Gutierrez-Osuna, R. Using Heart Rate Monitors to Detect Mental Stress. In Proceedings of the 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks, Berkeley, CA, USA, 3–5 June 2009; pp. 219–223. [Google Scholar]
[18] Xu, T.; Cullen, K.R.; Houri, A.; Lim, K.O.; Schulz, S.C.; Parhi, K.K. Classification of Borderline Personality Disorder based on Spectral Power of Resting-State fMRI. In Proceedings of the 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 26–30 August 2014; pp. 5036–5039. [Google Scholar]
[19] Iqbal, T.; Redon-Lurbe, P.; Simpkin, A.J.; Elahi, A.; Ganly, S.; Wijns, W.; Shahzad, A. A sensitivity analysis of biophysiological responses of stress for wearable sensors in connected health. IEEE Access 2021, 9, 93567–93579. [Google Scholar] [CrossRef]
[20]]Iqbal, T.; Elahi, A.; Redon, P.; Vazquez, P.; Wijns, W.; Shahzad, A. A review of biophysiological and biochemical indicators of stress for connected and preventive healthcare. Diagnostics 2021, 11, 556. [Google Scholar] [CrossRef] [PubMed]
[21] Sadad, T.; Bukhari, S.A.C.; Munir, A.; El-Sherbeeny, A.M.; Rauf, H.T.; Ghani, A. Detection of Cardiovascular Disease Based on PPG Signals Using Machine Learning with Cloud Computing. Comput. Intell. Neurosci. 2022, 2022, 1672677. [Google Scholar] [CrossRef] [PubMed]
[22] Zhao, Y.; Bergmann, J.H.M. Non-Contact Infrared Thermometers and Thermal Scanners for Human Body Temperature Monitoring: A Systematic Review. Sensors 2023, 23, 7439. [Google Scholar] [CrossRef] [PubMed]
[23] Akmandor, A.O.; Jha, N.K. Keep the Stress Away with SoDA: Stress Detection and Alleviation System. IEEE Trans. MultiScale Comput. Syst. 2017, 3, 269–282. [Google Scholar] [CrossRef]
[24]]Aileni, R.M.; Valderrama, C.; Pasca, S.; Strungaru, R. Skin Conductance Analyzing in Function of the Bio-Signals Monitored by Biomedical Sensors. In Proceedings of the 2016 International Symposium on Fundamentals of Electrical Engineering (ISFEE), Bucharest, Romania, 30 June 2016–2 July 2016; pp. 1–4. [Google Scholar]
[25] Winiarz, E. Endorphins, Endocannabinoids and Runners' High. Sci. J. Lander Coll. Arts Sci. 2019, 13, 4. [Google Scholar]
[26] Wang, H.; Zhang, Y.-f.; Xu, L.-l.; Jiang, C.-m. Step rate-determined walking intensity and walking recommendation in Chinese young adults: A cross-sectional study. BMJ Open 2013, 3, e001801. [Google Scholar] [CrossRef] [PubMed]
[27] Madhuri, V.J.; Mohan, M.R.; Kaavya, R. Stress Management Using Artificial Intelligence. In Proceedings of the 2013 Third International Conference on Advances in Computing and Communications, Cochin, India, 29–31 August 2013; pp. 54–57. [Google Scholar]
[28] Abdullah A.AI-Atawi,Saleh Alyahyan on " stess monitoring using machine learning , IoT wearable sensors.