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A CNN BASED FOOD FRESHNESS CLASSIFICATION

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ABSTRACT:

Freshness detection of fruits plays a pivotal role in ensuring food quality and safety. In this study, we propose a Convolutional Neural Network (CNN) based approach for automatically detecting the freshness of fruits from images. Our method leverages the power of deep learning to extract meaningful features from fruit images, allowing for accurate classification of freshness levels. We construct a dataset comprising images of various fruits at different stages of freshness, annotated with corresponding freshness labels. The CNN architecture is trained on this dataset using a supervised learning approach.

Keywords: Convolutional Neural Network (CNN),deep learning.

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I INTRODUCTION

In today's food industry, ensuring the quality and safety of produce is paramount, with freshness being a key determinant of consumer satisfaction and health. However, traditional methods of assessing fruit freshness are often subjective and labor-intensive, prompting the need for automated solutions leveraging advancements in deep learning technologies. This study introduces a novel approach utilizing Convolutional Neural Networks (CNNs) for the automated detection of fruit freshness from images. By harnessing the power of CNNs, which excel at extracting intricate patterns and features from visual data, we aim to develop a robust system capable of accurately classifying fruits into different freshness levels based solely on their visual appearance. The proposed system addresses the challenges associated with manual freshness assessment by constructing a comprehensive dataset comprising annotated images of various fruits at different stages of freshness. Through supervised learning, the CNN model learns to discern subtle visual cues indicative of freshness, enabling it to make precise freshness predictions. This research not only contributes to advancements in food quality assurance and safety but also holds promise for streamlining supply chain management processes and reducing food wastage, ultimately benefiting both producers and consumers alike.

II. LITERATURE SURVEY

TasmimaAkter[2022] works on"Local Vegetable Freshness Classification Using Transfer Learning Approaches".

Proposes a novel approach to assess the freshness of vegetables through automated computer vision systems. By employing the DenseNet201 Transfer Learning model, the research achieved impressive results, attaining a test accuracy of 98.56% in categorizing vegetables into fresh, aged, and rotten classes. This work highlights the potential.of transfer learning in automating the detection of vegetable freshness, reducing human reliance, and enhancing the quality control process in the food industry.

J N V D TanujaNerella [2023] introduced “Performance Comparison of Deep Learning Techniques for Classification of Fruits as Fresh and Rotten”.

This study is focused on the classification of fruits as fresh and rotten, crucial for the agricultural industry. It evaluates various deep learning models, such as ResNet50, MobileNetV2, VGG 16, and InceptionV3, with InceptionV3 outperforming the others with an accuracy of 97.1%.

Chai C. Foong [2021] introduces "Convolutional Neural Network based Rotten Fruit Detection using ResNet50"

Explores the detection of rotten fruits and focuses on the classification of bananas, apples, and oranges. By implementing the ResNet50 model, the research achieved a high validation accuracy of 98.89%. The study emphasizes the significance of deep learning and CNNs in addressing the challenges of fruit quality control. The fast processing time, approximately 0.2 seconds per fruit image, is a notable advantage for practical applications in the food industry.

Prof.SarikaBobde [2021] introduced a " Fruit Quality Recognition using Deep Learning Algorithm".

Freshness is the most critical indicator of fruit quality, and directly impacts consumers 'physical health and their desire to buy. Also, it is an essential factor in the price in the market. Therefore, it is urgent to study the evaluation method of fruit freshness. Taking banana as an example, in this study, we analyzed the freshness-changing process using transfer learning and established the relationship between freshness and storage dates. Features of banana images were automatically extracted using the Google Net model and then classified by the classifier module. The results show that the model can detect the freshness of bananas and the accuracy is 98.92%, which is higher than the human detecting level. To study the robustness of the model, we also used this model to detect the changing process of strawberries and found that it is still useful.

Shobana G,[2022] works on "Fruit Freshness Detecting System Using Deep Learning and Raspberry PI".

This research addresses food quality checking and fruit freshness detection using deep learning and machine vision. It integrates various deep learning and machine learning algorithms with a Raspberry Pi, aiming to provide a recommendation system for blind individuals.

Subash. S. I. [2023] introduced "A Novel and Efficient CBIR using CNN for Flowers".

This paper discusses the application of Convolutional Neural Networks (CNNs) in flower image classification and retrieval, addressing challenges in content-based image retrieval (CBIR). It aims to improve the accuracy and specifications of image retrieval using CNNs.

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III SYSTEM ANALYSIS

EXISTING SYSTEM

In many cases MOS (metal oxide semiconductors) sensors have been used since they are readily available on the market and suitable for use due to their robustness, rapid response and good sensitivity to volatile compounds in a recent work, novel optical and gas sensors for fish quality assessment and their detection mechanisms have been described , however, the development of an enose system specifically designed to be applied for a rapid and easy inspection of fish in the supply chain was not considered.

Limitations of Existing system

- Reliance on a Neural Network model alone for freshness classification may limit accuracy, particularly with complex visual data like food images.
- Lack of specialized feature extraction tailored to image analysis tasks may hinder the effectiveness of the classification model. Lack

PROPOSED SYSTEM

The proposed system is an electronic nose employing a Convolutional Neural Network (CNN) to classify food freshness. It consists of a miniaturized MOX gas sensor array, a CMOS integrated circuit (1.5×1.5 mm), and a CNN-based classification unit. Time series features extracted from sensor signals enhance freshness classification accuracy. The system achieves 97.3% accuracy for 20 food types, with a 6.5% improvement due to time series feature extraction, emphasizing its significance for precise classification.

Proposed system Advantages:

- To design a classification model that reduces human efforts.
- To implement Machine Learning algorithms for classification of fruits.
- To detect or identify FRESH/ROTTEN fruits
- Efficiency high.
- Accuracy High

IV IMPLEMENTATION

A system architecture or systems architecture is the conceptual model that defines the structure, behavior, and more views of a system. An architecture description is a formal description and representation of a system. Organized in a

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way that supports reasoning about the structures and behaviors of the system.

Architecture:

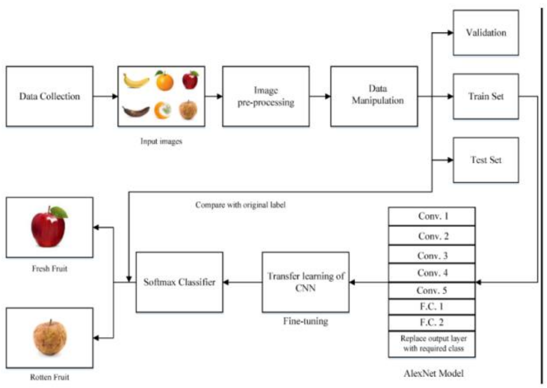

Fig-1. Architectures of the system model

CNN Architecture, Process & Inputs

Architecture: CNNs contain a combination of layers which transform an image into output the model can understand.

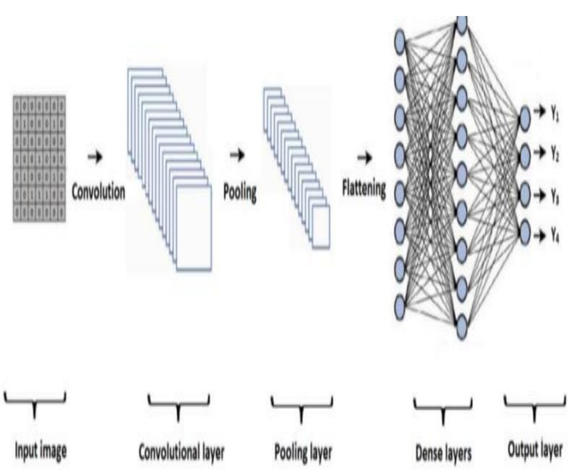

Fig-2. CNN Architecture

- Convolutional layer: creates a feature map by applying a filter that scans the image several pixels at a time

- Pooling layer: scales down the information generated by the convolutional layer to effectively store it

- Fully connected input layer: flattens the outputs into a single vector

- Fully connected layer: applies weights over the inputs generated by the feature analysis

- Fully connected output layer: generates final probabilities to determine the image class.

Process:

Forward and backward propagation iterate through all of the training samples in the network until the optimal weights are determined and only the most powerful and predictive neurons are activated to make a prediction.

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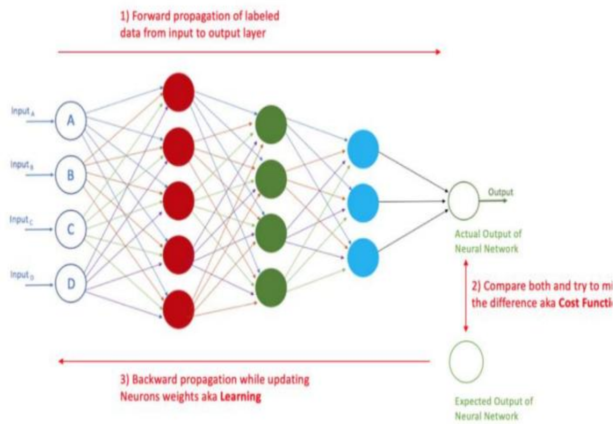

Fig-3. Cnn Process

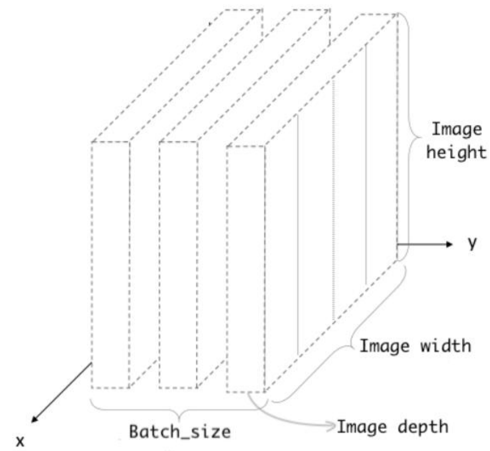

Fig-4. Inputs

- The model trains throughout many epochs by taking one forward and one backward pass of all training samples each time

- Forward propagation calculates the loss and cost functions by comparing the difference between the actual and predicted target for each labeled image

- Backward propagation uses gradient descent to update the weights and bias for each neuron, attributing more impact on the neurons which have the most predictive power, until it arrives to an optimal activation combination.

Inputs:

Model inputs always have to be in a 4D array consisting of (batch size, height, width, depth)

- Batch size: The number of training examples in one epoch (the higher the batch size, the more memory you'll need)

- Height & Width: Pixel dimensions of your image

- Depth: Red, Green or Blue (3), or Black & White (1)

System Design Plan

The system design planned in this study can be seen in Figure 5.In preparing the data, the public dataset Fresh and rotten fruit for classification has been collected and the dataset has been divided into two parts, namely training data and testing data. The next process is pre-processing data by cropping, resizing the data as needed. The next process is training by designing a model that is planned to be used and a list of

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specified parameters such as the level of learning and the number of training epochs. In this process, accuracy is calculated using the loss function. The limitation for training data is limited to fresh apples, fresh oranges, fresh bananas, rotten apples, rotten oranges and rotten bananas so that the planned model can only predict these 6 classes. For the training process of CNN design,

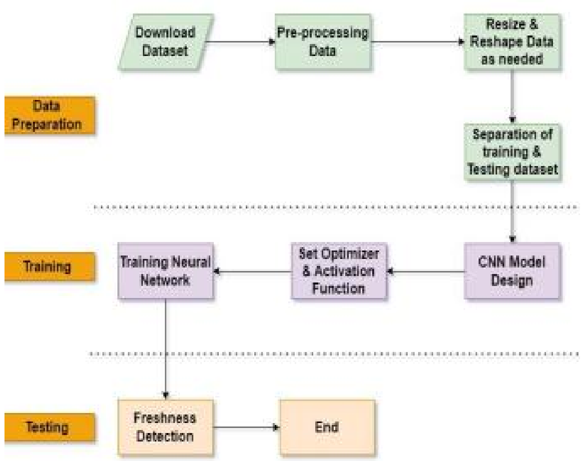


Fig 5: system design plan

SYSTEM WORKFLOW

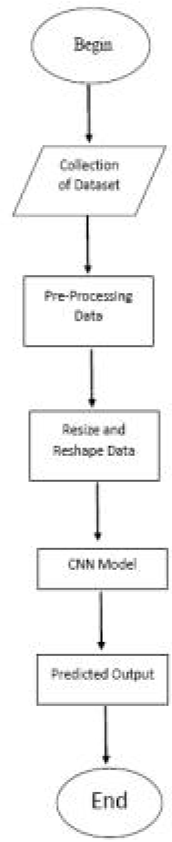
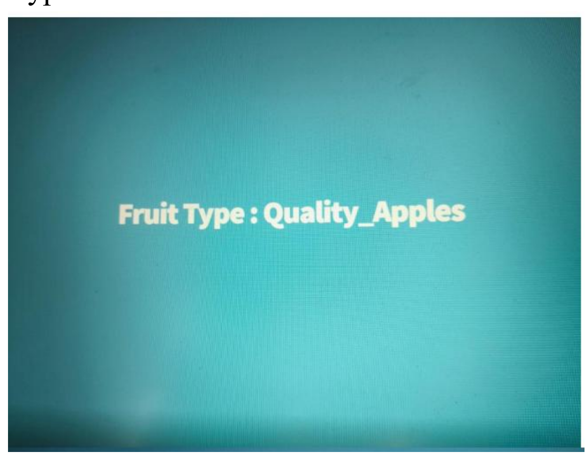


Fig-6: system workflow

V RESULT AND DISCUSSION

Fruit Type:



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Quality detection:

VI CONCLUSION

In conclusion, this project has demonstrated the potential of integrating advanced technologies such as odor monitoring, electronic noses, and Convolutional Neural Networks (CNNs) to address the critical issue of food spoilage detection and freshness assessment. Through the exploration of various methods and approaches outlined in the referenced literature, significant progress has been made in developing effective systems for tracking and identifying food spoilage in diverse settings, including smart homes, food processing facilities, and agricultural environments. The adoption of CNNs for freshness classification represents a notable advancement, offering enhanced accuracy and reliability compared to traditional methods. By leveraging CNNs' ability to extract complex features from food images, this project has demonstrated the feasibility of achieving precise freshness assessment with improved performance. Furthermore, the incorporation of IoT devices and real-time monitoring systems presents opportunities for scalable and efficient freshness detection, enabling proactive intervention to mitigate food spoilage and ensure consumer safety. In summary, the findings of this project underscore the importance of technological innovation in addressing food spoilage challenges, with potential implications for enhancing food quality, reducing waste, and optimizing food supply chain management processes. Continued research and development in this field hold promise for further advancements in food freshness assessment and quality control practices, ultimately contributing to a safer and more sustainable food system.

FUTURE ENHANCEMENT

These extensions for enhancing food freshness classification with CNNs encompass multi-modal fusion, transfer learning, data augmentation, attention mechanisms, TCNs, uncertainty estimation, domain adaptation, interactive systems, privacy-preserving techniques, continuous learning, ensemble methods, and explain

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ability, collectively enhancing model accuracy, robustness, and interpretability.

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