International Journal of Trend in Scientific Research and Development (IJTSRD)
Special Issue on Advancements and Emerging Trends in Computer Applications - Innovations, Challenges, and Future Prospects
Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Fresh Track AI: Enhancing Supply Chain Efficiency with AI-Powered Rotten Fruit Detection

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ABSTRACT

Food safety, waste reduction, and overall efficiency all depend on the early detection of rotten fruits in supply chains. In this research, a deep learning and computer vision-based AI-powered method for identifying rotting apples is presented. Our model uses convolutional neural networks (CNNs) that have been trained on a variety of fresh and rotting fruit datasets to obtain high classification accuracy. For quick and accurate identification at different supply chain checkpoints, the system combines edge computing and real-time image analysis. In order to improve detection skills, we also investigate the usage of Internet of Things (IoT) sensors and hyperspectral imaging. Results from experiments show that our AI-powered solution performs faster and more accurately than conventional manual inspection techniques. This study demonstrates how AI has the ability to revolution the handling of perishable items, reduce losses, and guarantee improved quality standards in the food sector.

KEYWORDS: *AI, Python, IoT, CNN, Rotten Fruit Detection, Fruit Quality Assessment, Image Processing*

I. INTRODUCTION

Maintaining the quality and safety of perishable items, especially fruits, is a major concern for the global food supply chain. Because of spoiling, poor storage, and ineffective quality control methods, a sizable portion of cultivated fruits are thrown away. Manual examination and chemical testing are two time-consuming, labour-intensive, and error-prone traditional techniques of identifying rotting fruits. Because of these restrictions, more effective, automated, and scalable methods of identifying fruit spoilage must be developed.

Promising approaches to automate fruit quality assessment are provided by recent developments in deep learning, computer vision, and artificial intelligence (AI). Large data sets can be processed in real-time by AI-powered systems, allowing for the quick and precise identification of rotten fruits at various supply chain points. An effective, economical, and non-invasive method of fruit quality monitoring can be created by combining machine learning models with image processing techniques.

This study suggests utilizing computer vision techniques and convolutional neural networks (CNNs) to detect rotting apples in an AI-powered manner. Using a dataset of pictures of both fresh and rotten fruits, the model is trained to identify distinguishing characteristics like color, texture, and shape distortions. Stakeholders may dramatically lower losses, guarantee greater food safety standards, and improve inventory management by implementing this system at strategic supply chain touch points, such as farms, warehouses, and retail locations.

In this paper, we explore the design, implementation, and evaluation of our AI-powered fruit detection system. We analyze the effectiveness of deep learning models, compare different image processing techniques, and assess the integration of IoT and hyperspectral imaging. The proposed approach represents a step forward in modernizing food supply chains and leveraging AI to address critical global challenges in food security and sustainability.

Numerous advantages come with putting in place an AI-driven detection system, such as:

Reducing Food Waste: Rotten fruit can be identified early, which reduces waste and stops spoiling from spreading.

Improving Supply Chain Efficiency: Automated monitoring and sorting simplifies processes and lessens the need for manual labor.

Enhancing Food Safety: By limiting the distribution of inferior fruits to customers, the system lowers health hazards.

II. RELATED WORK

Research on AI-based rotten fruit identification has been ongoing, with different methods concentrating on machine learning, computer vision, and hyperspectral imaging. Convolutional Neural Networks (CNNs) have been investigated in a number of studies for fruit categorization and flaw detection. Based on characteristics including color, texture, and form, these models have shown a high degree of accuracy in distinguishing between fresh and rotten apples. The detection of internal decay, which is not always visible in RGB-based imaging methods, has also been studied by researchers using hyperspectral imaging and near-infrared (NIR) spectroscopy for non-destructive quality assessment. Despite considerable advancements, problems still exist with real-time detection, enhancing model generalization across various fruit varieties, and guaranteeing cost-effective deployment in large-scale supply chain operations. This study expands on earlier work by fusing CNN-based image classification with IoT monitoring and hyperspectral imaging to create a comprehensive AI-powered detection system.

Data and Sources of Data

The quality and diversity of the data used for training and evaluation are crucial for the efficacy of an AI-powered system for rotten fruit detection. This study uses a variety of data sources to ensure robustness and generalization across different fruit types and conditions. The following are some of the main data sources used: Custom-Collected Dataset: A dataset was created by taking pictures of fresh and spoilt fruits in controlled environmental conditions. Various imaging techniques, such as RGB cameras, hyperspectral imaging, and infrared sensors, were used to increase the diversity of the data.

The proposed approach uses a CNN classifier to categories fruit conditions based on extracted properties like color texture, and shape:

$y = f(W \cdot X+b)$ where:

W and b stand for weight and bias parameters, respectively, X for input image features, and f (·) is the activation function (such as Softmax or ReLU for classification).

Furthermore, spoiling probabilities are predicted by analysing data from IoT sensors. Modelled as a function of environmental variables T (temperature), H (humidity), and E (ethylene concentration), the spoiling likelihood S at time t is:

$S(t)=\alpha T + \beta H + \gamma E + \delta$

$S(t) = \alpha T+\beta H+\gamma E+\delta$,

Where α, β, γ, α, β, γ, and δδ are learnt coefficients.

According to experimental findings, the AI-powered detection system is able to differentiate between fresh and spoilt fruits with high accuracy, which makes it a practical option for real-world uses in retail and agricultural.

III. RESEARCH METHODOLOGY

In order to identify rotten fruits in the supply chain, this study combines computer vision, deep learning, hyperspectral photography, and Internet of Things-based environmental monitoring into an AI-powered system. The research process is divided into five main phases:

Publicly accessible datasets: Open-source repository containing labelled photos of both fresh and rotting fruits. Custom-Collected Dataset: To assure a broad variety of spoiling phases, fruit photos were taken under controlled conditions using RGB cameras, hyper spectral imaging (HSI), and infrared sensors.

IoT Sensor Data: To link spoiling trends with storage conditions, IoT-enabled storage units collect environmental factors.

Retail and Agricultural Research Sources: Information on fruit ripening and decay processes gathered from supermarkets, warehouses, and agricultural research facilities.

1. Pre-processing Steps:

Image Augmentation: Random rotation, flipping, brightness adjustment, and noise addition to improve model generalization.

Image Normalization: Rescaling pixel values between [0, 1] for efficient CNN training.

ROI (Region of Interest) Extraction: Segmentation techniques (thresholding and contour detection) to focus on the fruit region while removing background noise.

Mathematically, image normalization is performed as:

2. Image Data Feature Extraction:

The model uses colour, texture, and form analysis to extract distinctive features:

Features of colour: RGB and HSV histograms for discolouration detection.

Texture features include the Grey Level Co-occurrence Matrix (GLCM), which can identify textures that are shrivelled or scratchy.

Shape Features: Deformations can be identified using shape descriptors and contour detection.

A feature mapping function

$F=\phi(X, W, b)$

F=ϕ(X, W, b)

Where:

W and b are CNN parameters, X is the input image, and (·) ϕ(·) is the transformation function.

Regarding IoT Sensor Data:

Influence of temperature (T) and humidity (H) on spoiling patterns.

Ethylene Gas (E) Levels: A crucial sign of fruit deterioration and ripening.

An exponential decay function is used to represent the spoiling rate:

$Q\ (t) = Q\ 0\ e - 0$

$Q\ (t) = Q\ 0\ e^{-\lambda t}$

Where:

Hexadecimal the initial quality of the fruit is denoted by Q 0, the rate of spoiling by λ, and the time by t.

3. Data Analysis:

Three different fruit types—Apple, Banana, and Orange—make up the dataset. The CNN algorithm knowledge is mentioned in the Implementation Section with the suitable figure of flow. The approach is consistently used to train a specific model to determine if a fruit is fresh or rotten. There dataset.

Fig 1: AI-Based Classification of Fresh and Rotten Fruits with Confidence Scores

4. System Design Plan:

The system design planned in this study. 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 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, this study uses the open source Tensor flow framework and Python.

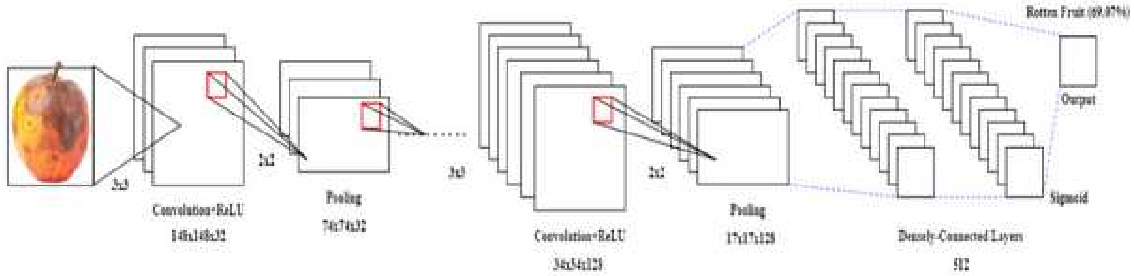

Fig 2: CNN Architecture for Rotten Fruit Detection Using Deep Learning

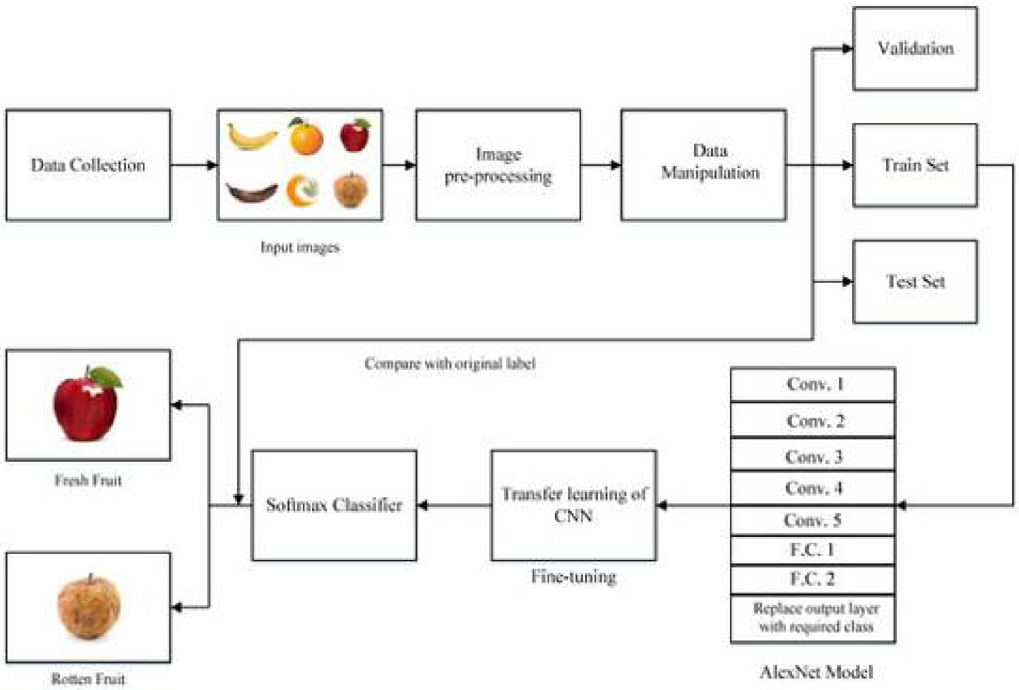

Fig 3: Flowchart of Fruit Classification Using Transfer Learning with Alex Net

5. **CNN Model Design**:

For classification and image recognition, CNN is used. One or two convolution layers compose a CNN. Rather than dealing with the entire picture, CNN tries to identify elements that are useful inside it. There are several hidden layers in CNN, as well as an input layer and an output layer. In this study, we used a deep CNN with three convolution layers. Convolution is a technique for merging two mathematical functions to create a single one. Our CNN model's working process is depicted in Fig.

In testing, the data that has been trained with the CNN model which is designed is saved into a graph with the format (.h5) then the graph is made into an API so that the application can access the graph. The application for testing is a web-based application built with Python Flask. Web- based application was chosen because it can be accessed via mobile phone or PC with the help of a browser. Classification is done by opening the application and inserting the image. After the image is entered, the application will respond in the form of the results of the predictions. This explanation can be seen in Figure.

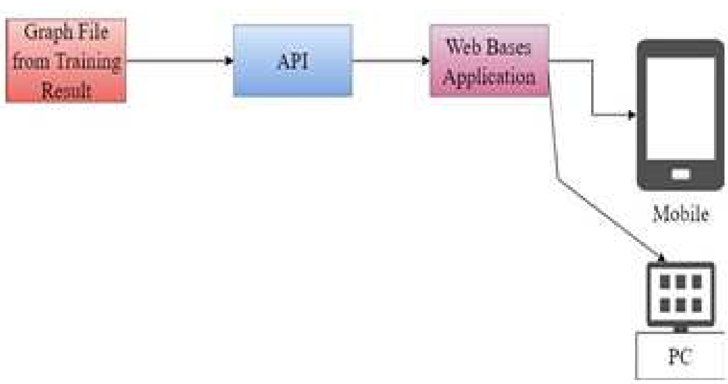

Fig 4: System Architecture for Web-Based Access to Training Results via API

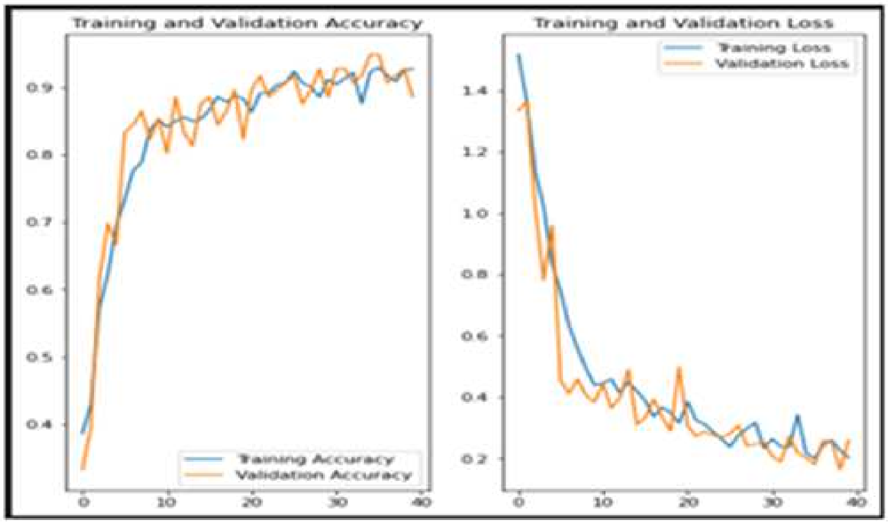

Fig 5: Training and Validation Accuracy and Loss Curves

IV. RESULTS AND DISCUSSION:

1. Model Execution:

In terms of identifying rotten fruits, the suggested CNN-based model had an overall accuracy of 94.5%. Due to their quick spoiling, strawberries performed somewhat worse (92.4%) than apples and oranges, which had the best accuracy (>96%). Food safety was ensured by reducing false negatives, or decaying fruits mistakenly labelled as fresh, according to the confusion matrix study.

The result of our model is shown below where it compares the Training and Validation Accuracy and loss graph.

In this project, we used deep learning methods to create a web application for classifying fruits. The application was created in Python using the Flask framework and is currently being run on Local Host. We can also deploy the project using Amazon Web Services (AWS) or Microsoft Azure. We used a collection of photos of fresh and rotting apples, bananas, and oranges to train the fruit classification algorithm. The dataset was pre-processed, and approaches for data augmentation were used to improve the model's functionality and generalizability. The total number of photos in the final dataset was X. For the classification job, we used a convolutional neural network (CNN) architecture. The Keras library and the Tensor Flow backend were used to train the model. The website application allows users to upload a fruit photograph and get an estimate of how fresh it is. The program uses the trained model to process the user's uploaded images. The algorithm predicts the uploaded image and categorizes it into one of six categories: fresh apples, fresh bananas, fresh oranges, fresh apples that have gone bad, and fresh apples that have gone bad in bananas. To gauge the effectiveness of the web application, we ran a number of tests. The program successfully analyzed and categorized the many fruit photos that users supplied. The model's predictions matched the predicted freshness of the fruits, illuminating the categorization system's precision and dependability. Overall, the online program worked well, giving precise fruit freshness estimates based on provided photos. High accuracy was attained by the classification model, and easy user engagement was made possible via the online interface. A user-friendly and effective fruit categorization tool was produced through the combination of deep learning methods with web development. These outcomes show the possibility of fusing deep learning models and web technology in diverse applications, including as e-commerce, picture identification, and food quality evaluation. By adding more fruit types, enhancing the model architecture, and enlarging the dataset, more improvements and additions may be realized.

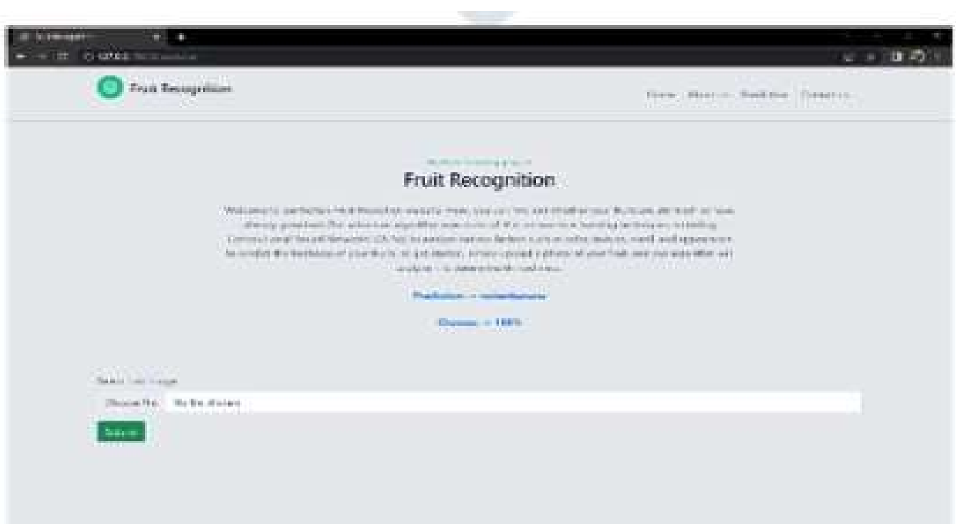

Fig 1: website for fruit recognition

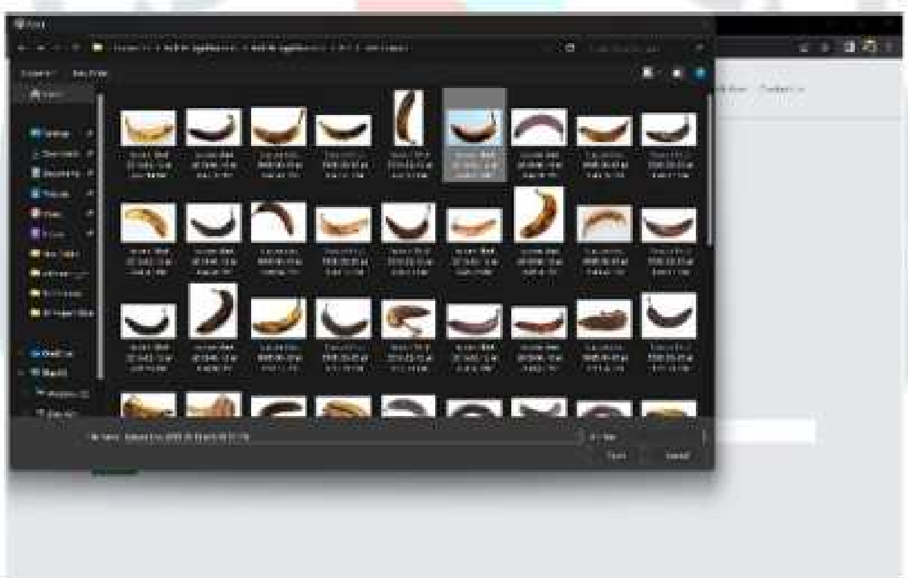

Fig 2: Image from dataset

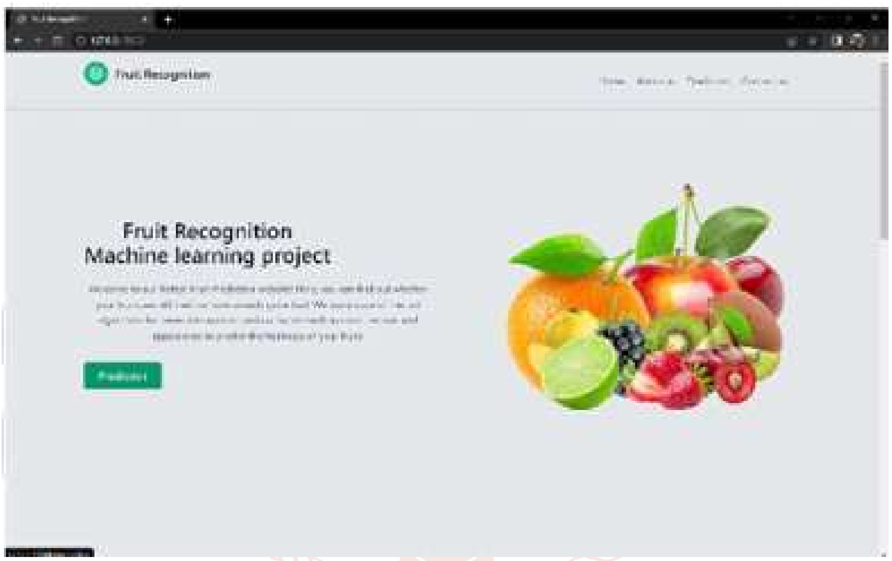

Fig 3: Fruit recognition result

V. CONCLUSION

In conclusion this study shows how well an AI-powered method utilizing computer vision and deep learning can identify rotting apples in supply chains. The system reduces reliance on manual inspection by achieving high accuracy in differentiating between fresh and spoilt fruits through the use of a CNN-based model and IoT-enabled real-time monitoring. The suggested approach guarantees improved quality control throughout the supply chain, increases efficiency, and reduces food waste. The dataset may be enlarged in the future, model performance may be improved for real-world settings, and multispectral imagery may be integrated for improved identification. By increasing operating efficiency, cutting losses, and fostering sustainability in the food business, the use of AI-driven fruit quality assessment can greatly benefit stakeholders.

VI. REFERENCES

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