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“Smart classification of fruits and vegetables using CNN and machine learning."

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Abstract -In order to improve automation in food processing, agriculture, and quality control systems, this research uses machine learning (ML) approaches to classify fruits and vegetables. To improve clarity and lower noise, we collected a large dataset of photos and used preprocessing. Even with a small amount of training data, we were able to obtain good classification accuracy by utilizing convolutional neural networks (CNNs) and utilizing transfer learning with pre-trained models like ResNet, Inception, and EfficientNet. Extensive tests showed great precision and recall utilizing both real-world situations and benchmark datasets. The system exhibits promise for use in inventory management, automated sorting, and crop monitoring, providing increased effectiveness and lower expenses.

***Key Words*: Machine learning, CNN, transfer learning, ResNet, Inception, EfficientNet, agricultural automation, food processing.**

1.INTRODUCTION

Our research focuses on classifying fruits and vegetables using machine learning (ML) to identify objects based on visual characteristics including texture, color, and size. We enhanced the pre-trained models through transfer learning to attain greater accuracy using Convolutional Neural Networks (CNNs) and sophisticated models like ResNet, Inception, and EfficientNet, which are renowned for their exceptional handling of intricate image features and high accuracy in visual tasks [1][4] We deal with issues like our skin's texture changing as we age and the seasons change. To get around these, we employed sophisticated preprocessing methods, such as data improvement, image normalization, and scaling, to make sure our models could generalize effectively well across different datasets [9]

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1.1 . Problem Statement

Traditional methods are based on human understanding, which leads to inconsistencies and inflexibility, especially given the rising demand for higher quality products. • Manually sorting fruits and vegetables is labor-intensive, time-consuming, and prone to errors due to variations in appearance. When it comes to scheduling, grading, and quality control issues, automated solutions are crucial for quick and accurate classification.

While machine learning-based classification algorithms offer potential solutions, they are constrained by factors like model robustness, pre-processing complexity, and dataset variety. To increase quality control, streamline operations, and satisfy industry standards for standardized products, a machine learning-based fruit and vegetable classification system that is more accurate and efficient is crucial. The resolution of the

1.2 Objective

The goal of this project is to create a machine learning (ML) system that can accurately and efficiently categorize fruits and vegetables according to their appearance. We hope to accomplish a number of important goals by employing transfer learning strategies with sophisticated convolutional neural networks (CNNs): Accurate ingredient identification: Despite the difficulties caused by differences in appearance resulting from ripeness, size, and physiology, we want to increase the accuracy of fruit and vegetable variety identification for the purpose of change. To guarantee that our system can accurately classify things in the actual world, this capacity is crucial. Enhance data quality: A key component of our strategy is the use of sophisticated pre-processing methods that enhance image quality and lessen the impact of noise. Techniques such as normalization, data enhancement, and image resizing are important for data preparation, and improve the visibility of our models.

Enhance model performance: We will modify pre-trained models like ResNet, Inception, and EfficientNet specifically for our classification task in order to achieve better results. We want to optimize the models' performance and guarantee a good fit for our particular data set by modifying the hyperparameters and choosing the best features.

System quality assessment: Extensive testing and validation is done using benchmark data sets and real-world data. This comprehensive evaluation process is critical to understanding the capabilities and limitations of our system, to ensure that it meets the desired standard of accuracy and efficiency.

Develop an automated distribution system: Ultimately, our aim is to apply the system developed in agriculture, in food production

2. Body of Paper

2.1 Literature Survey

Fruit and vegetable classification in agriculture, food processing, and retail has significantly improved thanks to machine learning (ML), particularly deep learning. While [2] stress preprocessing for improved accuracy[1] emphasize CNNs' efficacy in automation. In their comparison of ML approaches[3] find that deep learning performs better than conventional approaches. For better categorization, [4] talk about transfer learning using models like ResNet and EfficientNet. The automatic detection and grading of fruit utilizing color, texture, and shape data is the main topic of [5] [6] suggest automating agricultural robotics using deep learning. [7]create a retail identification system driven by machine learning.

[8] combine industrial sorting and packing with categorization. In order to improve ML performance[9] investigate preprocessing methods such as background subtraction[17] perform multi-class classification using SVMs and machine vision[19] concentrate on robustness against environmental fluctuations, [18] suggest deep learning for fruit recognition. CNNs and IoT are integrated [20] for real-time agricultural classification. These experiments show how ML can enhance agricultural monitoring, inventory control, and sorting. ML is revolutionizing agricultural automation and food processing with the integration of IoT and robotics.

Our work focuses on applying machine learning to identify fruits and vegetables in order to improve automation in food processing, agriculture, and quality control. To improve clarity and lower noise, we preprocessed a sizable collection of photos. Even with a small amount of training data, we were able to achieve good classification accuracy by using convolutional neural networks (CNNs) and transfer learning with models such as ResNet, Inception, and EfficientNet. Numerous tests showed excellent recall and precision on benchmark and real-world datasets. The system exhibits promise for use in crop monitoring, inventory control, and automated sorting, increasing productivity and cutting expenses.

Algorithm/Technique	**Dataset**	**Categories of Dataset**	**Accuracy**
VGG-16 and YOLO-v5	60059 images of 11 fruits and vegetables in 3 categories	Rotten, Fresh, Medium	Mean Average Precision of 84%
Naïve Bayes (NB), Linear Discriminant Analysis (LDA)	22495 images (100 × 100)	33 categories of vegetables and fruits	SVM classifier: 79.36%, Bagging: 60.34%. Order: Bagging > DT > SVM > LDA > NB
IoT, Deep Learning Process	20,000 images (96×96 pixels = 9216 pixels as input)	Fresh, Stale, Unripe	Accuracy of 90-95%
CNN_BiLSTM deep learning model (fusion of CNN and BiLSTM)	Six fruits and vegetables: apple, banana, bitter gourd, capsicum, orange, tomato	Fresh and Stale	Maximum accuracy of 97.76% in detecting the freshness of fruits and vegetables
PCA feature dimensionality reduction (affects SVM classifier)	12,000 images (~600 per category: 5997 fruit images for 10 classes, 6003 vegetable images for 10 classes)	Fresh, Rotten	Accuracy, Precision, Matthews Correlation Coefficient, and F1-score of 99.95%, 100%, 99.48%, and 1.00 for fresh strawberries
CNN Deep Learning	8072 images of more than 350 date bunches from 29 date palm varieties	Naboot Saif, Khalas, Barhi, Meneifi, Sulla	Achieved final accuracies of 99.01%, 97.25%, and 98.59% .

CNN model, YOLOv4	12,000 images of 5 fruits and 5 vegetables (20 classes, image	Fresh, Rotten	73.5% and 72.6% for fruits and vegetables

Fig no: 01 Literature Survey Table

2.2 Workdone

2.2.1 Methodology

Dataset

We collected images of various fruits and vegetables from publicly available online databases such as Kaggle and personal image collections. The dataset includes high-resolution images of different fruits and vegetables in various lighting and environmental conditions. (Nawaz et al., 2020). This diversity helps in improving model generalization and robustness.

Classification of fruits and vegetables:

Information Gathering: Gather pictures of different fruits and vegetables from websites, internet databases, and private collections. Data preprocessing: Clear the pictures and eliminate any extraneous details or ambient sounds. To balance color and brightness, resize photos to a uniform size and normalize them.

Feature Extraction: To extract significant features from preprocessed photos, apply methods like convolutional neural networks (CNNs). Basic characteristics like size, color, and shape are captured by these features.Model selection: Pick machine learning models that are suitable for the classification problem. CNNs are the best models for the image classification task. To take advantage of pre-existing information, think about employing transfer learning with pre-trained models like ResNet, Inception, or EfficientNet.

Training samples: Create training and validation sets using labeled data. To reduce the classification error, train the chosen model using the training set while adjusting the model's parameters. To guarantee sufficient generalization over the unseen data, test the model's performance on a validation set.
Model evaluation: Use metrics like accuracy, precision, recall, and F1-score to assess the trained model's performance. Evaluate the model's ability to categorize fresh photos using different test data.
Application and testing: To evaluate the trained model's suitability for real-world uses, place it in authentic environments like commercial marketplaces or agricultural processing facilities. Get input and make necessary revisions to the model to handle any issues that may arise during implementation.

2.2.2 Flowchart:

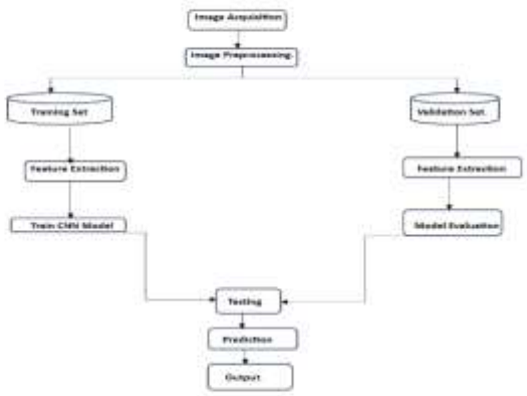

Fig no.02 Flowchart of Image Classification using CNN

Explanation:-
The process begins with image acquisition, where fruit and vegetable images are collected to build the dataset. Next is image preprocessing, which involves resizing the images to a consistent dimension, normalizing pixel values, and applying data augmentation techniques to improve model generalization. After preprocessing, the dataset is divided into a training set, which is used to teach the model. During training, feature extraction is performed using Convolutional Neural Network (CNN) layers to identify and learn essential patterns from the images. The CNN model is then trained using this training data to classify the images accurately. Additionally, a validation set is created from the dataset to fine-tune the model's parameters and prevent overfitting. After training, the model undergoes evaluation using the validation data to assess its performance. Following this, testing is carried out on a separate set of unseen data to confirm the model's effectiveness in real-world scenarios. Finally, the model is used for prediction, where it outputs the predicted class of a fruit or vegetable along with a confidence score, and the result is displayed to the user.

2.2.3 Requirements

- Operating System : Windows 10+, Mac, Linux
- RAM : minimum- 8GB
- Graphic cards: GTX 1650 and above
- Python Version: 3.12
- Processor: Intel i5 and 12 gen eqivalent and above
- Google Colalb
- Compiler: VS code or any equivalent
- Machine learning Libraries : TensorFlow
- Dataset

2.3 OUTPUT

Fig : 2.3.1 A dashboard view of the "Fruits & Vegetables banner featuring various fruits and vegetables, providing an overview of the interface.Recognition System" with a vibrant

Fig: 2.3.2 Project overview with dataset details and folder structure.

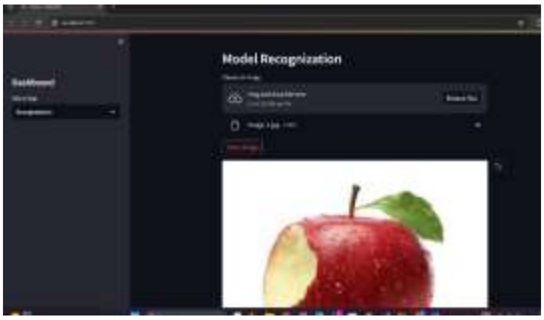

Fig: 2.3.3 Model recognition interface showing a bitten apple image.

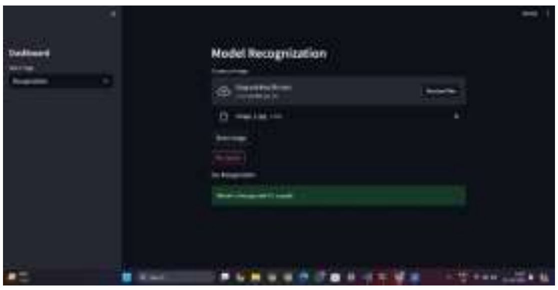

Fig 2.3.4 Model recognition interface showing Details of the given input image

3. CONCLUSIONS

A machine learning model for fruit and vegetable classification from photos was created as part of the research. To improve model performance, a variety of datasets were gathered and pre-processed to guarantee consistency. Convolutional Neural Networks (CNNs) were chosen for their ability to classify images well; during evaluation, they produced good performance metrics and high accuracy, indicating robust generalization. To increase the accuracy and dependability of the model, more fine-tuning was done. Ultimately, the model was used for real-time categorization, allowing for effective automation in applications related to food processing and quality control.

3.1 Conclusion

Our project demonstrates the feasibility and effectiveness of using machine learning for fruit and vegetable classification, addressing critical needs in agriculture and food processing. Despite challenges, our smart system accurately identifies and sorts produce, promising streamlined operations. Moving forward, we're dedicated to refining and expanding its capabilities through ongoing research and development, aiming to enhance accuracy, efficiency, and adaptability. Ultimately, we aim to provide a reliable tool for increased productivity and quality control in the agricultural sector, marking an important advancement in automated produce sorting with far-reaching implications for food production processes..

3.2 Future scope

By eliminating the need for manual labor, machine learning-based fruit and vegetable classification can greatly help grocery businesses. The technology can automatically create bills and identify fruits and vegetables by automating the detecting process. In addition to expediting the checkout process, this lowers human error and improves transaction accuracy and efficiency. Additionally, by assisting customers and employees in differentiating between similar-looking products, the machine learning model can guarantee that the right things are billed and priced appropriately. All things considered, this technology simplifies retail operations, which enhances customer satisfaction and lowers operating expenses.

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