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Fruit Quality Analysis Using Its Skin Texture

Om Itankar[1], Sakshi Nirmal[2] , Prajwal Meshram[3], Prof. Nilesh Korde[4]

[1,2,3] Students, [4]Assistant Professor, Department of Computer Engineering SVPCET, Nagpur

nkorde@stvincentngp.edu.in

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Abstract—: *This paper focuses on the importance of image quality in fruit classification and certification processes, underscoring the significance of meticulous data collection in crafting robust learning models for this purpose. To address this necessity, we introduce the "FruitNet" dataset, which concentrates on six widely recognized Indian fruits. The FruitNet database comprises over 14,700 high-resolution images, categorized into three groups: "High Quality Fruit," "Low Quality Fruit," and "Mixed Quality Fruit." Each category includes images of apples, bananas, guavas, lemons, oranges, and pomegranates, all captured using a mobile phone equipped with a high-resolution camera. These images were intentionally captured against various backgrounds and lighting conditions to mirror real-world scenarios. This dataset serves as a valuable asset for training, testing, and refining fruit classification or recognition models. With its comprehensive collection of images, the FruitNet dataset facilitates the development of machine learning algorithms tailored to fruit analysis tasks.*

I. INTRODUCTION

To solve the problem of classification and recognition of fruits, it is important to get a good picture of the fruit. Well-designed data is the foundation for building the right learning model. Keeping this goal in mind, we created the "FruitNet" dataset, which focuses on six well-known fruits in India. The file contains more than 14,700 high-resolution images of this fruit and is carefully divided into three subfolders: "High Quality Fruit", "Low Quality Fruit" and "Mixed Quality Fruit".

Each subfolder contains images of six different fruits: apple, banana, guava, lemon, orange and pomegranate. Images were taken using mobile phones with high-resolution, sharp and detailed cameras. Additionally, images are captured in different backgrounds and lighting to simulate real-life scenes. The FruitNet dataset is intended to be a useful resource for training, testing and analyzing fruit or pattern information. By providing diverse and comprehensive images, these data facilitate the development of powerful machine learning algorithms for fruit analysis tasks.

This article highlights the importance of fruit identification and classification in various fields.Fruits are important sources of vitamins and fiber and play an important role in human nutrition .But of the more than 2,000 types of fruit around the world , only a few are widely recognized. Analysis of the fruit shows a massive global production, led by China, India and Brazil.

Advances in agricultural technology, especially fruit identification, have given hope to farmers and ordinary people. These machines can also be used for children's education. Using computer vision and deep learning techniques, these systems can facilitate object detection and semantic segmentation of the image.

Several important works on automatic fruit recognition and classification are discussed, many of which use deep neural network learning. For example, a study focused on vegetable identification achieved approximately 95.50% accuracy using a convolutional neural network (CNN). Other studies have used various techniques, including neural networks and fuzzy logic, for the identification of citrus defects and achieved high classification. Similarly, in the research conducted on Indian fruits, approximately 95% accuracy was achieved using TensorFlow-based CNN models.

A study using different CNN architectures in olive classification revealed that the best result of Inception-ResNetV2 was 95.91% accuracy. Other functions explore different types of fruit classification, including BPNN, SVM, and CNN, with CNN showing the most accuracy.

Some research projects combine image processing and machine learning techniques. Fruit recognition, for example, uses image processing to achieve approximately 90% accuracy in calculating the geometric shape of the fruit. Another study uses image processing technology and Gaussian Naive Bayes algorithm to classify fruits with high

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accuracy.

In addition, some projects continue to distribute fruit to areas such as disease testing and smart agriculture. For example, one study successfully used MobileNetv2 to detect diseases in the leaves of trees. Others focus on identifying plant diseases using machine learning techniques and artificial intelligence to help improve agriculture.

Together, these different studies demonstrate the potential of advanced technology for fruit classification and its wider applications, including disease testing and agricultural development.

II. LITERATURE SURVEY

Evaluation of fruit quality has historically relied on peer-reviewed literature, which has led to a lack of consistency and requirements, especially in large production areas. However, in recent years, people have started to turn to image processing technology to obtain quality measurements by extracting features from fruit images. This process involves classification, extraction, and sorting algorithms that identify features such as color, size, and shape[1].

The emergence of deep learning, particularly convolutional neural networks (CNN), has revolutionized the use of computer vision, including the analysis of fruit quality. CNNs show promise in easily learning from images, providing more accurate and useful results. Researchers have begun to use deep learning and image processing techniques in agriculture, especially in fruit measurement. This technology demonstrates the ability to accurately identify and classify fruit based on factors such as ripeness, blemishes, and other characteristics[6].

Despite the potential, challenges remain, such as limited data diversity, difficulties in generalizing models across different fruit species, and adaptation to different environments. Key findings include the effectiveness of deep learning models, especially CNNs, in achieving greater accuracy and efficiency compared to traditional image processing techniques. Successful applications include identifying fruit defects, classifying fruits based on various characteristics, and distinguishing different fruit types.

The study, which used a pre-learning model to assess fruit quality, showed promise in improving quality standards and overcoming the hurdles of dealing with small data. Additionally, the integration of IoT devices and cloud computing is being explored to improve instant monitoring and optimization of fruit quality measurement[7].

Future advances in fruit quality assessment using image processing and deep learning will require more detailed data representing different fruit types and conditions to improve the performance, efficiency and versatility of deep learning models in different situations. To ensure the reliability of these models under different lighting conditions and backgrounds, it is important to pay attention to environmental changes. There is also an urgent need to develop tools for customers suitable for practical use in agriculture, such as factories and plant distributors[2].

Finally, although significant advances have been made in the use of image processing and deep learning to evaluate fruit quality, it is important to conduct further research and development, particularly focusing on different data, model robustness and practicality gender.

The use of image processing and deep learning to evaluate fruit quality has made many contributions:

Quality control automation:
An important combination of image processing and deep learning Evaluation of fruit quality recommended and features such as maturity, defects, size and color can be evaluated. Fast and accurate evaluation with advanced algorithms.

Improved accuracy and performance:
Deep learning models, especially convolutional neural networks (CNN), outperform traditional imaging techniques in terms of higher results and runs on measurement. This model is good at distinguishing between different fruits and characteristics and allows for further evaluation.

Detection and classification:
Significant improvements have been made in detection and classification, allowing the identification and classification of bruises, mold and other defects in fruit. Deep learning models have shown remarkable accuracy in distinguishing between normal and abnormal fruits[3].

Adaptability to different environments
Through research, people are committed to improving the adaptability of these systems to different environments and discovering ways to improve the performance of the model in different lighting, backgrounds and environments. Dynamic process ensures reliability and efficiency in different situations.

Transformation Applications:
The use of pre-trained models allows researchers to overcome problems arising from limited data and increase the efficiency and effectiveness of evaluating fruits.

Potential Applications:
Many studies have investigated the use of this technology in agricultural areas such as fruit trees, nuts, and distribution centers and have shown that agricultural use is shifting more towards consumers. and Can use the distributed system.

Used together, these important advances demonstrate the evolution of image processing and deep learning in fruit evaluation as the basis for accurate measurement and purpose in agriculture[6].

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III.PROPOSED METHODOLOGY

A method that uses image processing and deep learning together was adopted to analyze fruit quality. At first, different information about the shape of the fruit was obtained from different species, conditions and characteristics. The data is then subjected to pre-processing including modelling, transformation, normalization and augmentation to improve its quality and diversity. Image processing techniques are then used for video extraction, including color analysis, texture analysis, image description and segmentation to isolate specific areas of the image. Flaw detection and classification algorithms have been developed to detect defects such as bruises, mold or irregularities in fruit. Then, select and use an appropriate deep learning architecture, specifically a convolutional neural network (CNN), to train the models using the prepared data. Hyperparameters and training iterations are optimized to achieve high and high performance in fruit quality analysis. The model's performance is measured and validated using cross-validation methods to assess comprehensive and robust capacity for many different types of data, as well as a variety of metrics such as accuracy, precision, recall, F1 score, and confusion matrix. This system is then deployed in real-life environments, such as a fruit processing plant or distribution center, for real-world testing to evaluate its effectiveness and efficiency. Based on feedback from actual evaluations, investigate improvements and optimizations, including learning transitions and optimizations, to improve standards well done. A comparative analysis was conducted to compare the deep learning model with traditional methods and imaging techniques used to evaluate fruit quality. The research results are presented through clear, accurate graphs and comparisons to demonstrate the best and most effective methods of the proposed method, providing its overall evaluation and practical application in real agriculture.

1. Information Collection and Preparation:
- Compiled from different fruit images happy for 6 popular Indian fruits: apple, banana, guava, lemon, mango, orange and pomegranate.
- To facilitate analysis, the organization divides images into three subfolders: good, bad, and mixed by good fruit.
- Take photos and make changes to the background and lighting using a mobile phone with a high-resolution camera.

2. Data Processing and Enhancement:
- Using techniques such as resizing, normalization and color correction, preliminary images are made to look the same and improve the quality of the data.
- Improved dataset and illumination by introducing changes in orientation and scale to simulate real life and increase model robustness.

3. Model selection and training:
- Consider factors such as model complexity and computational efficiency to choose a suitable deep learning model for fruit classification and work experience.
- Introduces model selection, optimizes comparison, and training iterations for optimal performance using a complete set of algorithms.

4. Measurement and Evaluation:
- Evaluate model performance and provide quality assurance across many different information sources using metrics such as accuracy, precision, recall, and F1 score.
- Be sure to test the model's ability to perform efficiently and robustly in different environments.

5. Distribution and Application:
- Embed the training model in real applications such as fruit distribution for business, retail sales and equipment acquisition training.
- Use web and mobile technology to enhance user interaction to facilitate easy access and use of the distribution.

6. Future Developments:
- Explore deep learning and strategies to improve search and segmentation while improving resource utilization.
- Expanded data to include different fruit types and different shapes, improving model detail and real-world usability.
- Search for apps that can detect bad or damaged fruit and provide recommendations for smart farming.

In conclusion, the scheme shows the way to use fruit shape image to create a powerful learning model for classification and information processing. By following this approach, researchers can contribute to the advancement of fruit-related trade and agriculture, ultimately promoting productivity and innovation in this field.

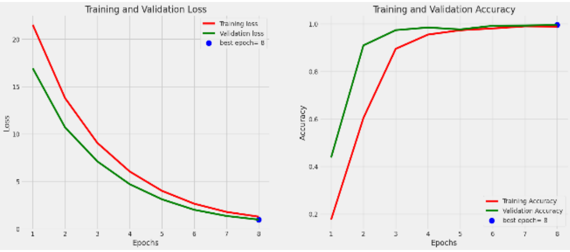

Fig.1 Feature importance graph

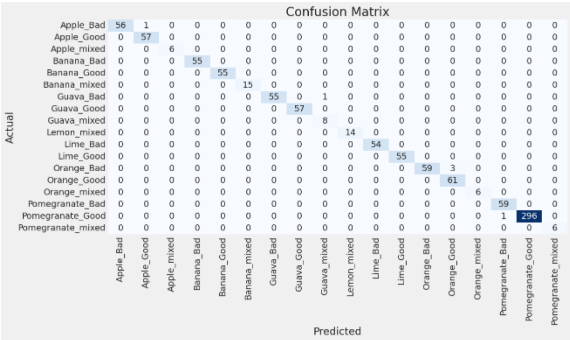

Fig.Confusion Matrix

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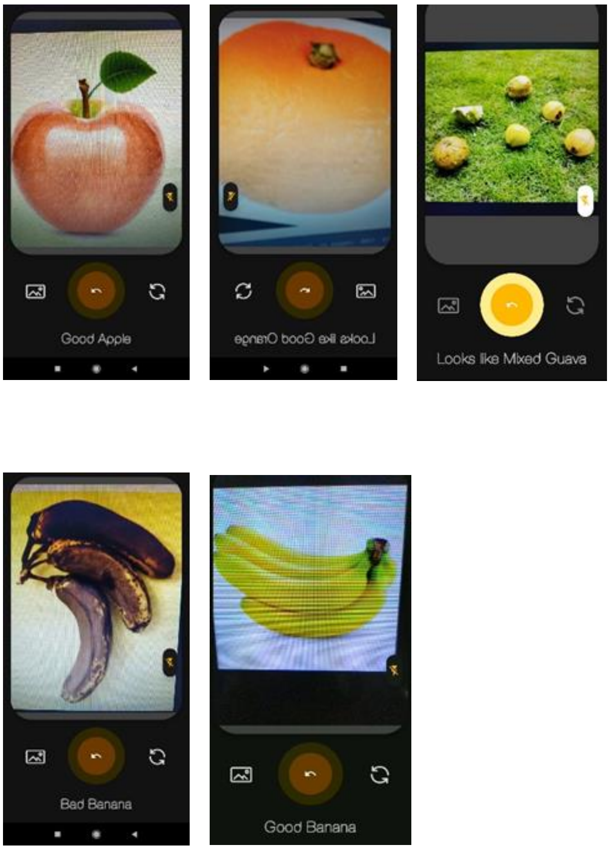
IV. RESULT



V. CONCLUSION

In summary, the development of the "FruitNet" data set is an important step in meeting the need for quality information in fruit classification and identification activities. With over 14,700 hand-picked images representing six popular Indian fruits, FruitNet provides an essential resource for researchers and developers in the machine learning community.

Carefully sorting good, bad and mixed quality images into subfolders according to fruit quality improves the value of the file and its relevance to real-world events. Images in FruitNet are captured using highresolution mobile cameras in different background and lighting conditions, providing a diverse and detailed representation of the fruit.

By simplifying the training, testing and validation of fruit classification and recognition standards, FruitNet allows researchers to develop more accurate and powerful algorithms. FruitNet is therefore well placed to promote progress in the fruit industry and agriculture, ultimately helping to increase profitability and efficiency in these areas.

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