CAPSTONE PROJECT

FRUIT QUALITY ASSESSMENT USING DEEP LEARNING

PRESENTED BY

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PROBLEM STATEMENT

A leading fruit supply company has approached **FruitScan Solutions** to develop an automated solution that can distinguish between fresh and rotten fruits in real-time using image input from their supply belt. The supplier, primarily dealing in apples, oranges, and bananas, faces challenges in ensuring consistent fruit quality, often resulting in customer complaints due to the inclusion of rotten fruits in purchased baskets. Manual sorting is slow, inconsistent, and not scalable. The company seeks to increase the speed and accuracy of their quality control process by integrating a computer vision-based system that can automate fruit classification and help streamline their distribution workflow

FRUITSCAN
SOLUTIONS

PROPOSED SOLUTION

To address the challenge of accurately and efficiently sorting fruits, we propose an automated fruit quality assessment system powered by deep learning. The solution leverages a pre-trained VGG16 convolutional neural network, fine-tuned to classify images of apples, bananas, and oranges as either fresh or rotten. The system uses static images captured from the supply belt for training and validation, ensuring robust and reliable classification performance.

- **Data Collection:**
  - **Collected the collection of images of fresh and rotten banana, apple and orange from Kaggle .**
  - **The labelled dataset used is - Fruits fresh and rotten for classification**
- **Data Preprocessing:**
  - **All images were resized and normalized to ensure compatibility with the chosen deep learning model.**
  - **Data augmentation techniques, including rotation, flipping, and cropping, were applied to enhance dataset diversity and improve model generalization.**
  - **The dataset was systematically divided into training and validation subsets.**
- **Machine Learning Algorithm:**
  - **Transfer learning was employed using a pre-trained VGG16 convolutional neural network.**
  - **The classifier component of the model was modified to output six classes, corresponding to fresh and rotten categories for each fruit type.**
  - **The model underwent fine-tuning on the processed dataset to optimize classification performance.**
- **Deployment:**
  - **An automated pipeline was developed for the classification of static fruit images.**
  - **The trained model was saved to facilitate future inference tasks.**
  - **The system architecture was designed with provisions for future integration of live video feed classification using OpenCV.**
- **Evaluation:**
  - **The model's performance was evaluated using accuracy and loss metrics on the validation set.**
  - **Continuous monitoring was conducted to mitigate overfitting.**
  - **Instances of misclassification were reviewed to identify potential areas for further improvement.**
  - Result: The trained model acquired an accuracy of 99.44% in classifying the correct type and condition of fruit.

SYSTEM APPROACH

- **System Requirements:**
  - Python 3.8 or higher
  - GPU-enabled hardware (recommended for faster training)
  - Minimum 8GB RAM and 10GB free disk space
  - Operating System: Linux, Windows, or macOS
- **Libraries Required to Build the Model:**
  - **PyTorch**: For building and training deep learning models
  - **torchvision**: For pre-trained models and image transformations
  - **Pillow**: For image processing
  - **kagglehub**: For downloading datasets from Kaggle
  - **glob**: For file and directory operations
  - **os**: For operating system interactions
  - **Jupyter Notebook**: For interactive development and experimentation

ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
  - A transfer learning approach was adopted using the **pre-trained VGG16 convolutional neural network (CNN).**
  - **VGG16** was chosen due to its proven effectiveness in image classification tasks and its ability to extract robust features from visual data.
  - The model was fine-tuned to classify images into six categories: **fresh and rotten apples, bananas, and oranges.**
- **Data Input:**
  - The algorithm takes static images of fruits as input.
  - Each image is preprocessed (resized, normalized, and augmented) before being fed into the model.
  - The input data is labeled according to fruit type and quality (fresh or rotten).
- **Training Process:**
  - The model was initially trained with frozen base layers to leverage pre-learned features, then fine-tuned by unfreezing all layers.
  - The dataset was split into training and validation sets.
  - Data augmentation techniques were applied to improve generalization.
  - The **Adam optimizer** and **cross-entropy** loss function were used for optimization.
  - Model performance was monitored using **validation accuracy and loss**.
- **Prediction Process:**
  - The trained model predicts the class (fresh/rotten, fruit type) for new, unseen fruit images.
  - For each input image, the model outputs the most probable class label.
  - The current system processes static images, with future plans to extend prediction capabilities to real-time video feeds for live classification.

RESULT

The fine-tuned VGG16 model achieved high classification accuracy of **99.44%** on the validation dataset, demonstrating strong capability in distinguishing between fresh and rotten fruits across apples, bananas, and oranges.

Access the GitHub Repository of the project from **here.**

CONCLUSION

The proposed solution effectively classifies fresh and rotten fruits using a deep learning-based approach, leveraging transfer learning with the VGG16 model. The model demonstrated strong performance in distinguishing between six classes of fruits, achieving high accuracy on the validation set. Key findings include:

- **Effectiveness**: The use of transfer learning significantly reduced training time while maintaining high accuracy. Data augmentation improved the model's generalization to unseen data.
- **Challenges**:
  - Limited dataset size posed a challenge, mitigated by data augmentation techniques.
  - Fine-tuning the pre-trained model required careful adjustment of hyperparameters to avoid overfitting.
- **Potential Improvements**:
  - Expanding the dataset with more diverse images could further enhance model robustness.
  - Exploring other architectures like ResNet or EfficientNet may yield better performance.
  - Deployment optimization for real-time inference on edge devices could improve practical usability.

This project highlights the potential of deep learning in automating quality control processes, offering a scalable and efficient solution for the fruit supply industry.

FUTURE SCOPE

The current system is designed for static image classification but can be extended to real-time fruit detection and classification from live video feeds using **OpenCV**, enabling seamless integration into automated conveyor belt systems.

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Thank you