Convolutional Neural Networks for Fresh vs. Rotten Fruits Classification

CSC 462 Project Proposal

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1. Image Classification Task

1.1 Problem Definition

In this project, we aim to develop a binary image classification model using Convolutional Neural Networks (CNNs) to differentiate between fresh and rotten fruits. The ability to automatically classify fresh and rotten fruits is important for reducing food waste, improving food safety, and increasing efficiency in supermarkets and supply chains.

Manually sorting fruits is time-consuming, not efficient, and prone to errors[1], while a machine system can automate this process, ensuring only fresh produce reaches consumers. This technology can also help farmers, retailers, and researchers by providing a reliable way to evaluate fruit quality, prevent foodborne illnesses, and optimize inventory management.

The model will be trained on a self-collected dataset consisting of images of fresh and rotten fruits, ensuring diversity in lighting, angles, and backgrounds to improve real-world applicability. The classification task presents several challenges, including variations in fruit appearances, lighting conditions, and background noise, which could affect model performance.

2. Dataset Collection & Preprocessing

In this project, we use a dataset of fresh and rotten fruit images, collected through two methods: capturing personal photos at home and sourcing images from open-source platforms like Google Images and Kaggle. This combination ensures a diverse dataset with variations in lighting, angles, and fruit conditions, helping the model generalize better to real-world scenarios. The dataset is structured into training and validation sets, with at least 100 images per class for training and 50 images per class for validation. This setup provides the model with enough examples to learn meaningful patterns while allowing performance evaluation and hyperparameter tuning to prevent overfitting. Before training, images undergo preprocessing to ensure consistency and efficiency. All images are resized to 150x150 pixels, maintaining uniform dimensions for processing. Pixel values are normalized (0-255 → 0-1) to stabilize training and enhance model performance. To further improve generalization, data augmentation techniques are applied, artificially increasing the dataset size by at least 50%. These techniques include rotation to introduce orientation variations, horizontal flipping for mirrored perspectives, zooming to simulate size differences, and brightness adjustments to account for varying lighting conditions. These steps help the model recognize fresh and rotten fruits under different scenarios, making it more robust and effective in classification tasks.

3. Model Design & Implementation Plan

To effectively classify fresh and rotten fruits, a Convolutional Neural Network (CNN) is designed with a well-structured architecture that extracts meaningful features from fruit images. The model consists of three convolutional layers with 32, 64, and 128 filters, each using a **3×3 kernel size** and **ReLU activation function** to capture essential patterns such as color, texture, and decay indicators. To reduce dimensionality and improve computational efficiency, **MaxPooling (2×2)** is applied after each convolutional layer. Following the feature extraction, a fully connected **dense layer with 512 neurons** (using ReLU activation) further processes the learned features, leading to an **output layer with a single neuron using a sigmoid activation function** for binary classification, distinguishing fresh from rotten fruits.

To enhance performance, optional techniques such as **dropout** (to prevent overfitting) and **batch normalization** (to stabilize training) can be implemented. The model is trained using the **Adam optimizer** for efficient weight updates, with **binary cross-entropy loss** to optimize classification accuracy. The training process is conducted in batches of a specified size over multiple epochs to ensure the model generalizes well. The performance of the CNN is evaluated using **accuracy, precision, recall, and F1-score**, which collectively assess its ability to correctly classify fresh and rotten fruits. This structured approach ensures a robust and effective deep learning model for automated fruit quality assessment.

❖ Summary of Related Papers :

Summary 1 by Aliyah Aljarallah,

Palakodati et al. [1] propose a CNN-based model for classifying fresh and rotten fruits using a dataset of apples, bananas, and oranges and was divided into training (60%), validation (10%) and testing (30%). The model consists of three convolutional layers, with the first layer applying 16 filters (3×3 kernel size), utilizing random_uniform initialization and regularization to optimize learning. Each convolution layer is followed by max-pooling (2×2) layers to reduce parameters and computation time, while dropout (0.5) is applied to prevent overfitting. The second and third convolution layers use 16 filters with 5×5 and 7×7 kernel sizes, respectively. Extracted features are flattened and passed to a fully connected dense layer for classification. Hyperparameter tuning showed that a batch size of 16, Adam optimizer with a learning rate of 0.0001, and 225 epochs produced the highest accuracy. The proposed model achieved 97.82% accuracy, outperforming VGG16 (89.42%), MobileNet (68.72%), and Xception (78.68%). The findings confirm that a custom CNN model is more effective than transfer learning for fruit classification, emphasizing the importance of batch normalization, dropout, and fine-tuned hyperparameters. This study provides valuable insights for designing efficient CNN models for food quality assessment.

Summary 2 by Shoug Alsaleem,

Kazi and Panda et al. [2] propose a CNN-based model for classifying fresh and rotten fruits using apples, bananas, and oranges, split into training (99%), validation (1%), and testing (1%). They compare AlexNet, VGG-16, and ResNet50, with ResNet50 achieving 99.7% accuracy, outperforming AlexNet (99.3%) and VGG-16 (97.74%). Images were resized (150×150 pixels), normalized (0-255 → 0-1), and labeled, without background reduction. Hyperparameter tuning with Adam optimizer (learning rate = 0.0001), batch size 256, and early stopping improved efficiency. While ResNet50 showed superior classification, high computational costs and limited real-world testing were noted. This study highlights the effectiveness of deep learning in fruit classification, showcasing the advantages of residual networks for complex image features. It offers insights into model selection, preprocessing, and optimization. By applying these findings, our project can improve accuracy and efficiency while exploring background reduction and alternative CNN architectures for real-world use.

Summary 3 by Nouf Aljassar

The paper titled "Classification of Fruits Using Convolutional Neural Network and Transfer Learning Models" presents a study on classifying fruits as fresh or rotten using deep learning techniques, specifically Convolutional Neural Networks (CNN) and transfer learning models. The authors utilized a publicly available dataset named "fruit fresh and rotten for classification" from Kaggle, which includes images of various fruits in both fresh and rotten conditions.

In their methodology, the authors implemented a custom CNN model and compared its performance with transfer learning models based on pre-trained architectures such as VGG16, VGG19, Xception, ResNet50, and InceptionV3. The custom CNN model was trained from scratch on the dataset, while the transfer learning models were fine-tuned to adapt to the specific task of fruit classification.

The results indicated that the custom CNN model achieved a classification accuracy between 89% and 93.67%. This performance was compared to the transfer learning models, though the specific accuracies of these models were not detailed in the provided excerpt. The study highlights the effectiveness of using deep learning techniques, particularly CNNs and transfer learning, in accurately classifying fruits based on their freshness.

This research contributes to the field of agricultural technology by providing insights into automated fruit classification, which can aid in quality control and sorting processes in the fruit industry.[3]

References

[1] Palakodati, Sai Sudha Sonali, et al. "Fresh and Rotten Fruits Classification Using CNN and Transfer Learning." *Rev. d'Intelligence Artif.* 34.5 (2020): 617-622.

[2] Kazi, A., & Panda, S. P. (2022). Determining the freshness of fruits in the food industry by image classification using transfer learning. *Multimedia Tools and Applications, 81*, 7611–7624.

[3] Pathak, R., & Makwana, H. (2021). Classification of Fruits Using Convolutional Neural Network and Transfer Learning Models. Journal of Management Information and Decision Sciences, 24(S3), 1–12.