**Tomato Quality Prediction**

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*Abstract*—Tomatoes, a critical agricultural crop, are prone to diseases and pests that can significantly impact yield and quality. Traditional methods for assessing tomato health rely on manual inspection, which is both time-consuming and prone to error. This project explores an automated approach to tomato quality prediction using Convolutional Neural Networks (CNNs), leveraging a dataset of images categorized into "Fresh" and "Rotten" from Sher-e-Bangla Agricultural University. The CNN model, with its convolutional and max-pooling layers, efficiently classifies tomato quality after extensive preprocessing and augmentation. Performance metrics such as accuracy, precision, recall, and F1-Score demonstrate the model's effectiveness in identifying tomato health conditions. This automated approach aims to enhance crop management, reduce crop losses, and contribute to sustainable agricultural practices. The project's future vision involves integrating this technology with drones for real-time monitoring, enabling early detection of issues and promoting more efficient and sustainable agricultural operations.

# **Problem Identification**:

Tomatoes are a staple agricultural product with significant economic importance, but they are highly susceptible to diseases, pests, and environmental stressors. These factors can lead to considerable crop losses, reduced yield, and compromised quality. Traditional methods for assessing the health of tomato plants typically involve manual inspection by agricultural workers or experts. However, this approach has several inherent drawbacks: it is time-consuming, labor-intensive, and subject to human error. Furthermore, manual inspection may not always identify issues early enough for effective intervention, leading to further spread of diseases and additional crop damage.

**II.Data Preparation**

In preparation for building the Convolutional Neural Networ(CNN) model,we used the Keras ImageDataGenerator to handle data preprocessing and augmentation. This tool allowed us to normalize, rescale, and split our dataset, which consists of images of tomatoes categorized into two classes: "Fresh" and "Rotten."

The first step in data preparation was to normalize pixel values. We applied a rescaling factor of 1./255 to convert the original 0-255 pixel range to a 0-1 range. This normalization helps stabilize the training process, ensuring that the model receives consistent input data.Next, we created training and validation data generators with a 70/30 split, using the validation\_split=0.3 parameter to set aside 30% of the data for validation, while the remaining 70% was used for training

For the training data, the training\_generator was set up with a target image size of 240x240 pixels, a batch size of 32, and categorical class mode to support multiple classes. The images were loaded in color (rgb), and data shuffling was enabled to prevent the model from learning a specific order, promoting better generalization.

### The validation data was handled by the validation\_generator, which had similar configurations, but shuffling was disabled to maintain a consistent order for evaluation. Additionally, it was configured to fetch only the validation subset, ensuring that the data used for model evaluation remained consistent during training.

III. **Model Design and Implementation**:

**Convolutional Layers**

The model uses two sets of convolutional and pooling layers to extract features from the input images. The first convolutional layer has 32 filters, each with a 3x3 kernel size, and uses the ReLU activation function to introduce non-linearity. This layer's input shape is (240, 240, 3), corresponding to the image size and RGB color channels. It is followed by a MaxPooling2D layer with a 2x2 pool size, reducing the spatial dimensions while retaining essential features.

The second convolutional layer has 64 filters with a 3x3 kernel size, also using ReLU activation. Another MaxPooling2D layer with a 2x2 pool size follows to further reduce spatial dimensions, focusing the feature extraction process.

**Flatten and Dense Layers**

After the convolutional layers, the model uses a Flatten layer to convert the 2D feature maps into a 1D vector, allowing it to be fed into dense (fully connected) layers. The first dense layer contains 128 neurons with ReLU activation, providing high-capacity feature processing. A Dropout layer with a 50% dropout rate is added for regularization, reducing the risk of overfitting by randomly setting some neurons to zero during training. To further enhance stability, a BatchNormalization layer is included to normalize the outputs of the dense layer.

**Output Layer and Compilation**

The final output layer has two neurons with a softmax activation function, providing probabilities for the two classes, "Fresh" and "Rotten." The model is compiled with the Adam optimizer, known for its efficiency and adaptive learning rate, and uses the binary\_crossentropy loss function, suitable for binary classification tasks. The model's performance is measured by its accuracy.

**Model Training and Early Stopping**

The model is trained with a training generator, using the validation generator for validation data. The training process runs for up to 15 epochs, with the EarlyStopping callback set to monitor loss and stop training if there is no improvement for 3 consecutive epochs. This approach prevents overfitting and ensures the model doesn't over-train on the given dataset.

The training process involves continuous evaluation using the validation data to monitor the model's progress and adjust training accordingly. This approach, combined with early stopping and regularization, aims to deliver a robust and reliable model for predicting tomato quality.

**Model Loss and Accuracy**

![A graph of loss of a model

Description automatically generated with medium confidence]()![A graph with blue and orange lines

Description automatically generated]()

# **Evaluation and Testing**

Precision indicates the proportion of true positives among all positive predictions. A high precision suggests that the model rarely misclassifies a sample as belonging to a class when it doesn't. For the "Fresh" class, the precision is 95.26%, meaning that out of all tomatoes predicted as "Fresh," 95.26% were truly fresh. For the "Rotten" class, precision is 91.73%, indicating that among tomatoes predicted as rotten, 91.73% were actually rotten. This high precision minimizes the risk of false positives, avoiding the misclassification of fresh tomatoes as rotten and vice versa.

Recall reflects the proportion of actual positives that the model correctly identifies. A high recall is crucial for ensuring that most relevant samples are detected. For the "Fresh" class, the recall is 89.38%, indicating that the model correctly identified 89.38% of all actual fresh tomatoes. Although high, this level of recall suggests that there is a small risk of not identifying some fresh tomatoes, which could lead to unnecessary waste. Conversely, the recall for the "Rotten" class is 96.36%, demonstrating that nearly all rotten tomatoes were correctly detected, reducing the risk of spreading diseases due to undetected rot.

A diagram of a confusion matrix

Description automatically generated

The F1-score balances precision and recall, providing a single metric that combines both. The F1-score for the "Fresh" class is 92.23%, while for the "Rotten" class, it is 93.99%, indicating a good balance between precision and recall for both classes. This balanced approach ensures that the model is robust and reliable for practical applications.

Overall accuracy measures the proportion of correctly classified samples out of the total number of samples. The model's accuracy is 93.22%, indicating that it correctly classifies a large majority of the samples, further validating its reliability.

# **CONCLUSION**

Our project demonstrates the transformative potential of machine learning in addressing real-world agricultural challenges. By applying Convolutional Neural Networks (CNNs) to tomato health prediction, we aim to create a more efficient and effective method for crop management, ultimately reducing crop losses, improving yields, and promoting a more sustainable agricultural system.

One of the innovative aspects of this project is its potential for deployment in drones. Drones equipped with cameras and the trained CNN model can fly over tomato fields, capturing images and processing them in real-time. This capability allows for early detection of rotten tomatoes, enabling targeted removal or treatment. Such proactive measures can prevent further damage to crops, minimize the spread of disease, and reduce the need for manual inspections.

The use of drones with machine learning models could revolutionize agricultural practices by enabling automated crop monitoring and precise interventions. This approach may also serve as a blueprint for similar solutions in other crops and agricultural applications. We believe that the insights gained from this project will encourage further research and innovation in agricultural technology, paving the way for a more efficient, effective, and sustainable agricultural industry.

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