AI For Social Good: Using AI To Reduce Food Waste

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Introduction

According to the Environmental Protection Agency, food retail space and households wasted roughly 66 million tons of food in the United States. This is an important issue we face as a nation because as of 2022, there are approximately 44.2 million households in the US that are food insecure, making up about 12.8% of US households. Because of this, our group wishes to tackle the issue of food waste by using artificial intelligence algorithms such as Convolutional Neural Networks to help predict whether fruits are rotten or not by using image classification.

This relates to using artificial intelligence for social good because rather than throwing out fruits that may be rotten, users can take a picture and use our artificial intelligence algorithm to see if it is actually rotten or not. This can help reduce food waste because households, dining halls, and restaurants can use this to evaluate the status of their produce to determine if it is edible or not. If someone thinks a food is rotten but turns out it is not, that can signal to the user to consume that food immediately rather than letting it go to waste. However, if a food is deemed rotten, it can then encourage composting of the food rather than trashing it, further helping the environment and making use of unused or wasted food.

Some related work in this space include corporations such as Skip Shapiro Enterprises creating AI powered supply chain management systems to help grocers properly order the correct quantities of food as to limit food waste. However, our project focuses on analyzing if the fruit in someone's presence is rotten or not. Based on our experiment, we were able to accurately classify rotten and fresh fruits with an accuracy rate above 89% on our custom model, above 98% accuracy on our ResNet model, and above 99% on our MobileNet model.

Methods

The group approached this experiment by using a Kaggle dataset called the 'Fresh and Rotten Fruits and Vegetables Classification Dataset'. This dataset includes images of common fruits and vegetables such as apples, oranges, and tomatoes in various states of freshness.

Using Python and packages such as Keras, these images were preprocessed and augmented in three different load_data functions so that they could be passed into three Neural Network image classification models. The preprocessing steps used an 'ImageDataGenerator' from the Keras package which allowed for the automated augmentation and preprocessing of images.

After the preprocessing step, we decided to construct a custom Convolutional Neural Network model along with two pre-existing models named MobileNet and ResNet. These models were created through the usage of TensorFlow and Keras. The first custom model was created to be used as a baseline and to gain a better understanding of the dataset. The MobileNet model was then used because of its relatively small size that does not require large amounts of data to be efficient. We then used the ResNet model because it is a direct complement to the MobileNet model since it is larger in size and requires more data to be efficient. Below, figure 1 shows how these models are capable of discerning and extracting features from images of fruits and vegetables, which is crucial for our classification task. In the figure, the upper set captures basic details like edges while the lower set shows how the network begins to recognize more complex patterns such as shapes and textures. These features are used by each Convolutional Neural Network model to make a determination on whether or not produce is fresh or rotten. Each of these models are renowned for their image classification and by utilizing all three, the group was able to gauge which was most appropriate for our classification task. The final evaluation process involved using precision, recall, and accuracy metrics provided by Keras and a confusion matrix from Scikit-learn.

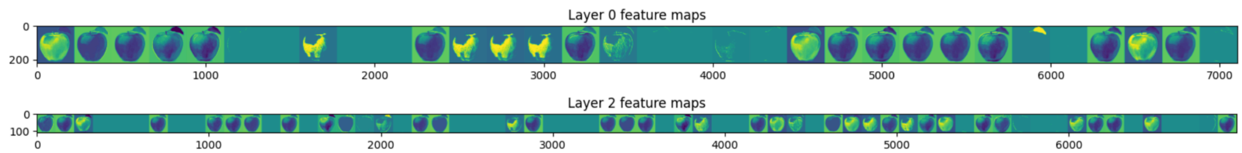

Figure 1: Visualization of Feature Map Extraction

Another Convolutional Neural Network that offers promising results is named Inception, or GoogleNet. This model uses a complex network of convolutional layers and could potentially offer better feature extraction capabilities at different image scales. We ultimately decided not to use this model because all of our images were the same size, making it unnecessary to experiment with such complexity. However, future research may focus on using this model to test its accuracy in detecting rotten and fresh produce, which could prove beneficial for automated quality control in different levels of the agricultural supply chain.

Data

This project utilized the publicly available "Fresh and Rotten Fruits and Vegetables Classification Dataset" sourced from Kaggle.com. The dataset comprises a collection of image files representing common fruits and vegetables such as apples, oranges, and tomatoes. Each item is captured in multiple images depicting different states of freshness. These images were used to train multiple classification models to determine if a fruit or vegetable is fresh or rotten. The data was split into a training set and a validation set, with 75% of the data assigned to the training set and 25% to the validation set.

Prior to training the classification models, the dataset underwent a series of preprocessing steps. The images were first resized to match the input size requirements of the three neural network models used in the project. This resizing ensured that each image was optimized for the capabilities of the corresponding neural network. After resizing, the images were augmented to diversify the dataset and reduce the possibility of overfitting. The augmentation techniques included rotations, shifts, zooms, and flips.

Experiments

In our project, we evaluated the performance of three deep learning models: a custom baseline Convolutional Neural Network, MobileNet, and ResNet50. We tested the validation accuracy of each of these models on a dataset of images that contained fresh and rotten produce. We used the preprocessing steps described above and ensured that each model was evaluated using the validation set.

The baseline model featured several convolutional, max-pooling, and dense layers, incorporating dropout to prevent overfitting. It also utilized an exponential decay schedule for the learning rate. The schedule started at 0.001 and decreased by 0.96 every 100,000 steps, with the Adam optimizer employed for training over 20 epochs.

For the MobileNet and ResNet models, we used pre-trained ImageNet weights, appending a global average pooling layer and a dense output layer with softmax activation to each. The training process for these models involved an initial phase where all pre-existing layers were frozen and only the new layers were trained. This was followed by a subsequent phase where all layers were unfrozen for comprehensive training. Each phase lasted 5 epochs, using a learning rate of 0.01 initially that eventually reduced to 0.0001 for fine-tuning. Also, the models were optimized using SGD with momentum and Nesterov acceleration.

The key parameters in our experiments included a batch size of 64 and varying epoch counts: 20 for the baseline Convolutional Neural Network and 10 for both MobileNet and ResNet50. We used categorical crossentropy as the loss function across all models. Using these experiments, we were able to evaluate the performance of our baseline model and transfer learning models in determining whether a food is rotten or fresh.

Results

After completing the training of all three models, we conducted an analysis of their performance. Our custom Convolutional Neural Network model achieved a validation accuracy of 89.91%. Despite having the lowest validation accuracy among the three, this model is beneficial due to its simpler architecture, which allows for easier modifications and scalability. It is particularly suitable for real-time applications where speed is crucial due to its lower computational demands and smaller size. Also, the training data revealed that the model starts with a low training accuracy of around 55% and gradually improves to 90.50%. The validation accuracy remained close to the training accuracy throughout the entire training process. This suggests that our custom model did not overfit the data and performed equally well on the training set and test set.

In contrast, the ResNet model reached a higher validation accuracy of 98.16%. It utilizes residual learning, enabling the training of deeper networks without the vanishing gradient problem, which helps in managing more complex visual tasks with higher accuracy. This makes it ideal for applications that require precise results but are less time-sensitive, such as in medical image analysis or manufacturing quality control. The training versus validation accuracy trends show a peak training accuracy at about 98.50% at the last epoch. Both the training and validation accuracy experienced some fluctuations, indicating potential initial overfitting. However, both accuracies were exceptionally high after the last epoch; therefore, the model performed well in classifying each class.

The model that performed the best was MobileNet, which had the highest validation accuracy of 99.39%. Designed for efficiency in mobile and edge devices, MobileNet uses separable convolutions that reduce the model size and computational costs while maintaining high accuracy. Both the training and validation accuracies of MobileNet display upward trends, with minimal gap between them, indicating strong generalization capabilities. This model is recommended for basic applications needing a balance between performance and operational efficiency, making it especially suitable for mobile applications and IoT devices. These characteristics show MobileNet's utility in settings where both high accuracy and efficiency are critical.

To help stakeholders visualize the results of these experiments, confusion matrices for each model are provided in the appendix. These visualizations clearly depict how well each model performs in categorizing test images across different classes. Based on the comprehensive performance data, we suggest adopting the MobileNet model for basic applications of determining whether fruits are rotten or not due to its optimal blend of high accuracy and efficiency. Below are graphs showing us the accuracy for all three models with both the training and test set.

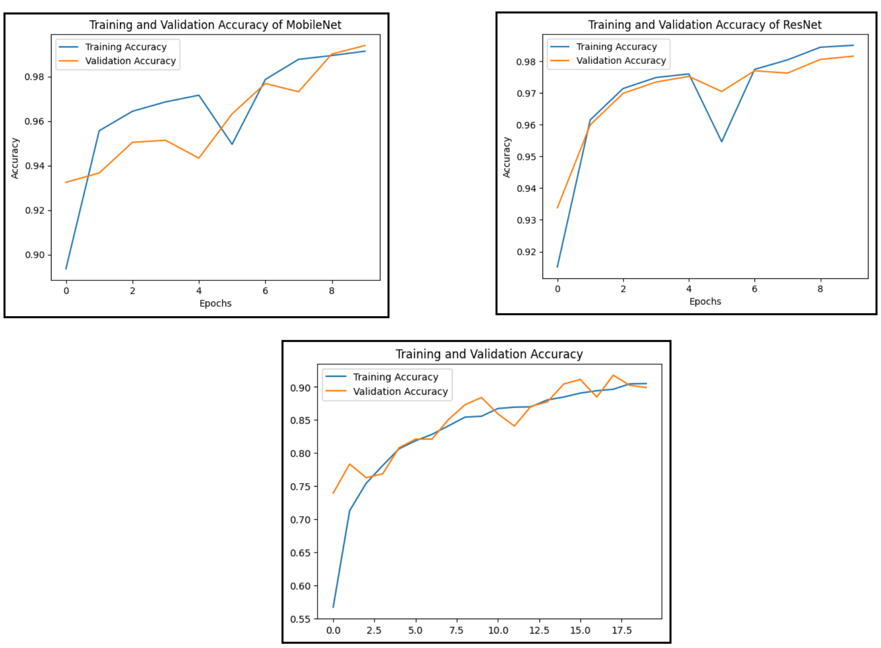

Figure 2: Training and Validation Accuracy of CNN Models

Since our task was a fine-grained classification task, it is worth discussing the difficulties that we faced when trying to distinguish between different stages of food decomposition. Fine-grained classification involves identifying subtle differences between highly similar categories. In our case, the categories were various stages of food spoilage, which can be visually close to each other, particularly in early stages of rotting where changes are minimal.

Our early models often struggled with this task, leading to higher misclassification rates between adjacent categories, such as classifying slightly spoiled food as fresh. We also noticed that cucumbers were being classified as okra and vice versa. Despite the high overall validation accuracies achieved by our three models, these subtleties in classification demonstrate the importance of enhancing feature extraction capabilities and potentially incorporating additional sensory data that allow for more accurate classification. The confusion matrices provided in the appendix further illustrate these challenges, showing specific areas where each model underperformed. In the future, training each model on a dataset that includes more precise stages of decomposition may increase the applicability of our technical solution.

Conclusion

Our project showed the potential of utilizing AI in addressing the issue of food waste. By using advanced image classification through Convolutional Neural Networks, we have developed a system that can accurately distinguish between fresh and rotten produce. This capability allows users to make informed decisions about food consumption and disposal, which allows them to reduce unnecessary waste.

The results of our experiment show that using Convolutional Neural Networks for our image classification task is effective. The MobileNet model was the most efficient, reaching a validation accuracy of 99.39%. This model offers a balance between performance and training time, making it ideal for practical application in mobile devices. We believe that integrating this technology in mobile devices is important because it is the most accessible way for users to take a picture of food to easily verify its freshness. The custom-built Convolutional Neural Network and ResNet models also showed strong performance, further showing the capability of using AI to solve food waste.

Throughout the project, we encountered and overcame various technical challenges, such as model overfitting and inadequate image preprocessing. These issues were addressed through changes in our methods, including the integration of advanced image augmentation techniques and optimization of learning rates to ultimately improve our models accuracy.

There are several future studies that others can engage in to improve our project and expand its scope. For instance, researchers could focus on expanding the dataset to include images with more varied and busy backgrounds. This change would better prepare the models for scenarios where food items are mixed with other objects. Additionally, exploring a wider range of AI models through transfer learning could reveal a more efficient AI model to use in the future. Finally, integrating this technology into mobile applications or devices commonly used in households and retail environments could streamline the process of checking food freshness.

This would enable our project to be used by the general public to help reduce the amount of food waste in both households and restaurants.

References

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Appendix

Link to Code in Jupyter Notebook:

https://colab.research.google.com/drive/12QcR9yM6Tot0kWeJI1Ijls7AES97rsDd?usp=sharing

Images of our Confusion Matrices: