Mango Classification System Using CNN

Paribesh Shrestha

Abstract—**In the Terai region of Nepal, mango grading is a big problem because the old manual methods are slow and often lead to inaccurate results. Following these old methods results in mixed quality, issues in grading and added problems for farmers, traders and consumers. In turn, farmers have trouble fulfilling orders and Nepal's export of mangoes is negatively affected. To deal with this, a CNN type Mango Classification System in Python has been designed. The system uses enhanced and correctly arranged image data to sort mango varieties effectively and correctly. The new CNN model is able to reach 98% accuracy for both training and validation sets, as well as has excellent precision, recall and F1-scores. The system accurately spots mango types and also separates non-mango pictures, therefore reducing chances of errors. It manages distribution of products for farmers in a reputable way, while fulfilling the requirements of both local and international quality. Because of quick image examination and documentation, the process becomes simpler and more effective for farmers. This technology makes classifying mangoes easy, reliable and fast, helping Nepal's agriculture and getting recognition for its modern farming methods.**

Keywords: Convolutional Neural Network(CNN),

I. INTRODUCTION

Agriculture is still a important sector in Nepal, accounting for national GDP of about 27% and employment to more than 60% of the country's population. Among many crops cultivated, mango is a major fruit crop with annual production of about 50,000 metric tons. In case of such large production, the mango sector is confronted with high post-harvest loss, non-uniform quality, and laborious manual sorting with around 25–30% losses and 40% misclassification. Just 15% of the mangoes are exported because of poor quality standards, which are owed to Nepal's decentralized supply chain and 65% farmers employing traditional hand-sorting techniques. These factors result in an estimated NPR 50–60 million annual loss and reducing consumer satisfaction, particularly in urban regions.

To combat such issues, in this work, the deployment of a CNN-based mango classification system is investigated. The system is directed towards enhancing sorting efficiency through the recognition of mango types, maturity stages, and defects for maintaining consistency, minimizing waste, and improving supply chain efficiency. This work paves the way for the widespread use of machine learning in Nepalese agriculture so that it becomes sustainable and competitive in the international market.

PROBLEM STATEMENT

Traditionally, mangoes are manually sorted and given a grade only by their appearance. However, this approach is slow, sometimes imprecise and error-prone. Because people have different ideas about mango quality, the standards used to classify them are not the same which then affects how well quality control is carried out. Having different standards reduces people's trust and may lead to a decline in sales, resulting in losses for all parties in the supply chain. With Convolutional Neural Networks (CNN), a deep learning system is now able to perform the task of mango classification automatically. There is a lot of mango image data that is used to train the system and before training, the images are first resized and normalized. After choosing the right hyperparameters, the CNN system accurately determines the type and quality of mangoes. This method greatly increases the efficiency, reliability and consistency in sorting mangoes instead of doing it manually. Because of this, it guarantees better monitoring of the product, makes the supply chain less dependent on people and increases how efficiently the items reach consumers.

II. PROPOSED SOLUTION

This project labels mangoes as to their type and quality using a Convolutional Neural Network (CNN) model. This approach makes training, evaluation and accurate classification easier and more efficient. The project relied on a standard way of working so that image preprocessing, model optimization and performance evaluation were always similar. With deep learning, mango sorting is done automatically, performing the task much faster and more dependably than sorting is when done by hand.

A. Data Cleaning and Preprocessing

For this project, a dataset with about 200 images per mango type was prepared to guide the training of the CNN. Every image indicates a certain type or grade of mango. To optimize the data for trainable models, an important preprocessing pipeline was put in place during the initial process. Image data augmentation was used to strengthen the ability of the model to solve various problems in the class. Training data was changed by applying rotations (up to 45 degrees), shifting the width and height by 15%, zooming by up to 20%, shearing, changing the brightness and both horizontal and vertical flipping. Emptied pixels were addressed in the results using both a channel shift and applying the fill mode feature. Such changes in the data recreate natural variability and reduce the risk of overfitting. In order to validate and test, standardization of pixel values was done with the preprocessing function only, with no extra adjustments made. As a result, test scores display the model's success on original examples.

Since the data was processed in a standard way, the CNN model was able to identify mangoes accurately and dependably in realistic situations.

B. Feature Extraction

Following preprocessing, feature extraction happened with the InceptionV3 model and its pre-trained ImageNet dataset. The deep CNN first uses convolutional where they are combined with pooling layers to classify objects from the input files. Using a GlobalAveragePooling2D layer, the spatial shape is changed to a length of 2048, still keeping key features.

After extracting the features, they go through a dense layer containing 512 units and dropout layer at a rate of 0.5 to strengthen learning and protect against overfitting. All images are made uniform using preprocess_input and augmenting the data makes the model learn a larger array of features and be more robust in training.

C. Model Training

Model training happened after the data was preprocessed and the features were extracted with the help of InceptionV3. The data for mangos was divided into training, validation and test sets and class weights were applied to make sure that all mango types were given equal importance. A warm-up stage was used at first, where InceptionV3 remained frozen but only the new dense and dropout layers were learning. Because of this, the model was able to learn how to classify mangoes without changing the original training weights. So, the next step was to unfrozen the first 50 layers of the base model for fine tuning. At this stage, the learning rate was decreased to properly shape the deeper elements of the model.

To enhance generalizability and improve the results of the model, extra training data was created and early stopping, reducing the learning rate and storing models at certain stages were also used. Thanks to these techniques, overfitting did not happen and the best results were preserved.

The system combined a warm-up phase with a fine-tuning phase to pick up both important and specific details, making the mango classification model trustworthy and accurate.

D. Model Validation and Evaluation

The results were evaluated using a confusion matrix and other important classification indicators such as accuracy, precision, recall and F1-score. The metrics come from checking the match between the predicted and given class labels for the test set.unknown data, resulting in higher reliability and classification accuracy.

- Accuracy represents the overall correctness of the model and is calculated as the ratio of correctly classified mangoes to the total number of test samples.

- Precision evaluates how many mangoes predicted as a particular class (e.g., "Mango A") were actually of that class, computed as TP / (TP + FP).
- Recall measures the model's ability to correctly identify all instances of a given class and is defined as TP / (TP + FN).
- F1-Score is the harmonic mean of precision and recall, providing a balanced evaluation metric especially effective in handling class imbalance.

For further analysis, a confusion matrix with normalized values and class-wise accuracy scores were prepared to portray accuracy rates for all types of mangoes. The model was accurate and did not change in its classifications among several categories, proving it can be reliably used for mango sorting.

E. Model Deployment

After finishing training the CNN model with InceptionV3, the training was saved and included in a Flask web application for live mango classification. Because of the deployment process, the trained model can be used several times and the results will not change.

In the software, users can share mango images or use a live webcam feed. Pretraining steps involve using the same pipeline and methods on all images: they are resized 299x299, turned to RGB and normalized using preprocess_input.

After the processing step, the loaded model receives the image, predicts the class of the mango and indicates the probability of its accuracy. Both the result and the image are shown to the user in an easy-to-use web interface.

The system can organize different types of mangoes and also sort out those that are not mangoes. We went with Flask since it is light, easy to set up and works well with TensorFlow models. With this application, the model can be used effectively in agriculture and business because it allows users to classify mangoes properly and swiftly.

IV. RESULTS AND DISCUSSION

This dataset has many images of different types of mangoes for the Mango Classification System. They are correctly marked and optimized to make sure the classification process works well. Accuracy, precision, recall and F1 score are some of the metrics that are used to assess the model's effectiveness in diagnostics.

A. Train And Val Accuracy And Loss

Fig: Train and Val Accuracy and Loss

The model's ability to learn is displayed by the shapes of its training and validation curves. The accuracy curve goes up in every epoch for both sets of data, finally plateauing at a high point which is a sign that the model is learning properly and can apply its knowledge to new examples. Likewise, the drop in loss curves for both sets of data continues steadily, staying close to each other and reaching stability as training goes on. Such behavior indicates that the model can learn a lot with only a small risk of learning too much. Though the curves reflect that the models are performing well, it's necessary to regularly check their performance to maintain how they work with new data. If needed, methods such as regularization, early stopping or changing hyper-parameters may be used to improve the model's stability and performance on fresh data.

B. Confusion Matrix

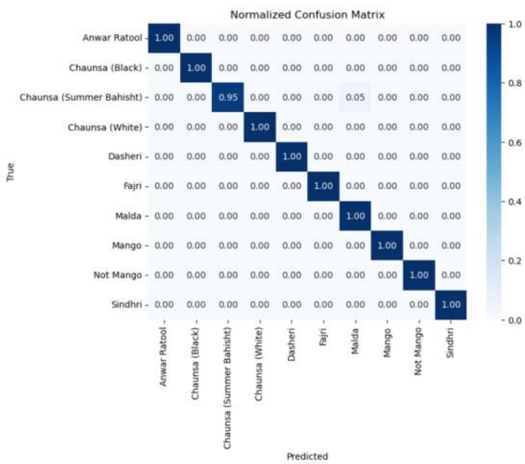

Fig: Confusion Matrix

The Confusion Matrix shows both the positives and negatives in the Mango Classification CNN model's performance. When the diagonal dominance is very close to 1.00, it shows that the model does a good job of correctly classifying most mango varieties. Out of 1,400 "Chaunsa (Summer Bahisht)" images, 5% were wrongly identified as "Malda" since the classes look alike or do not have sufficient details to tell them apart. The data seems well distributed between classes, however, increasing the data or fine-tuning the features may improve the model's accuracy. Tiny errors can sometimes be corrected using methods such as data augmentation, better features or better fine-tuning.

C. Classification Report

CNN is used in the classification report to thoroughly evaluate the Mango Classification System, pointing to its outstanding overall success with various classes. Precision scores are very strong and most types of mangoes receive a perfect 1.00, meaning the AI can predict and classify them accurately with few misclassifications. Malda's accuracy is set at 0.95, although this means it can occasionally mistake genuine cases as non-genuine. This model exhibits robust recall across various classes from its ability to distinguish true instances well. A recall of 0.95 for the "Chaunsa (Summer Bahisht)" class means the model is less likely to find all the correct labels. F1-scores are most commonly 1.00, revealing that precision and recall balance well. However, there are a few exceptions under "Malda" and "Chaunsa (Summer Bahisht)".

Classification Report:

	precision	recall	f1-score	support
Anwar Ratool	1.00	1.00	1.00	20
Chaunsa (Black)	1.00	1.00	1.00	20
Chaunsa (Summer Bahisht)	1.00	0.95	0.97	20
Chaunsa (White)	1.00	1.00	1.00	20
Dasheri	1.00	1.00	1.00	20
Fajri	1.00	1.00	1.00	20
Malda	0.95	1.00	0.98	20
Mango	1.00	1.00	1.00	5
Not Mango	1.00	1.00	1.00	15
Sindhri	1.00	1.00	1.00	20
accuracy			0.99	180
macro avg	1.00	0.99	0.99	180
weighted avg	0.99	0.99	0.99	180

Fig: Classification Report

The values of support indicate the number of samples used for each type of instance, offering a reflection on how reliable the metrics are. All in all, the model reaches a remarkable accuracy score of 0.99. For some classes that perform fewer than desired, techniques such as expanding data, separating features more clearly or making selected model changes may increase consistency.

V. CONCLUSION

In conclusion, the CNN-based Mango Classification System is a valuable advancement to agricultural technology and mango classification. The system's capability in classifying mango varieties with high accuracy from image data which it renders, provide highly beneficial for post-harvesting and supply chain management. Its consistent performance on real-time webcam analysis and static image upload demonstrates great potential for real-world implementation in fruit markets, packaging houses, and agricultural surveillance systems. Particularly in the case of Nepal and India, where mangoes hold great economic and cultural significance, this new approach stands to automate sorting procedures, reduce human error, and significantly boost overall productivity. The correct and swift categorization by the system ensures better inventory control, optimum fruit quality monitoring, and timely delivery of quality mangoes to local consumers and international markets.

VI. FUTURE WORKS

The development of a simple mango classification system is demonstrated in the final project. The system needs a lot of improvement and development in the agriculture of mango sector. The suggestions that follow recommendation for potential areas for further improvement:

- **Use of Larger Datase:** Having more varieties of mango images-captured in different light conditions, against different backgrounds, and from different angles-will make the system more robust and accurate in the real world. Having a greater variety of images will also help in more accurate classification.
- **Additional Features:** Investigate integrating complementary data including ripeness level, size, weight, and texture data to enrich the input to the classification. This will make the system more suitable for wider agricultural applications such as sorting and grading.
- **Improve Model Structure:** Repeatedly update the Convolutional Neural Network (CNN) structure. Methods such as fine-tuning and the use of more sophisticated models (e.g., EfficientNet, ResNet) can be used to improve overall performance and efficiency of the model.
- **Incorporate Real-Time:** Enhance the system to process real-time webcam footage or video streams to enable real-time mango classification. This can be facilitated through the development of a responsive interface and the inclusion of alert or decision-support mechanisms for effective deployment in farms, marketplaces, or sorting units.

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