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An Automated CONV-RFDNN Model Poised for the Differentiation and Identification of Diseases Impacting Mango Fruits through Transfer Learning

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Abstract: Fruit diseases pose a significant threat to crop yield and overall fruit quality. This research aims to address the challenges associated with the manual inspection process for identifying mango diseases. By leveraging advanced technology and image processing techniques, the proposed automated inspection system seeks to improve efficiency, reduce dependence on manual labor, and ensure timely detection of diseases. The findings of this research can potentially contribute to enhanced fruit quality and increased mango yield, ultimately benefiting global food security and human health. This study adopts an image classification approach to identify various diseases in mangoes and distinguish them from healthy specimens. The pre-processing phase involves the use of a Gaussian filter for noise removal. Following pre-processing, color-based segmentation (RGB Thresholding) is employed as a crucial operation. Subsequently, features are extracted using the VGG-19 model. The proposed model undergoes experimental verification and validation, demonstrating optimal outcomes with a precision rate of 98%. This high precision rate showcases the effectiveness of the Random Forest classifier in accurately categorizing mango images into different disease categories. The experimental results support the potential practical application of the model in the agricultural industry for disease detection in mango crops.

Keywords: *Mango Fruit, Deep Learning, Transfer Learning, Random Forest*

1. Introduction

Mangoes, a highly lucrative fruit extensively cultivated in tropical and sub-tropical regions worldwide, have gained immense popularity due to their enticing fragrance, delightful flesh, and substantial nutritional content. This widespread appeal has led to significant economic benefits for mango growers and countries that export the fruit. The value of a mango's economy is greatly impacted by its appearance. Typically, visually attractive mangoes are set aside for export, while those with less appealing looks are kept for local consumption. Mangoes deemed least desirable in appearance are often processed into canned fruit or jam. However, assessing mango quality has traditionally depended on laborious manual inspections. The time-consuming preservation process not only reduces the time for the profitable sale of fresh fruits but also poses the risk of human errors causing financial losses.

In collaboration with participants from the Taiwan AI CUP 2020, the present study aims to use advanced deep learning methods in computer vision, particularly CNN [1] – [4], to simplify and improve the grading process for mango growers. Our research focuses on a classification task that utilizes cutting-edge deep learning models known for their success in previous projects. These models include respected architectures like Alex Net, VGGs, and ResNets, all of which have excelled in the ImageNet Large Scale Recognition Challenge (ILSVRC). The ILSVRC [5] is a significant competition that deals with classifying a vast array of images into 1000 different categories. Additionally, the efficiency of transfer learning was investigated [6], which involves applying knowledge obtained from extensive datasets in general domains to specific domains with limited data. To execute this strategy, we utilize pre-trained weights from ImageNet, which are easily accessible via the torch vision package.

This study utilizes the CONV-RFDNN model to automatically detect and classify diseases in mango fruits. The process initiates with pre-processing, applying a Gaussian filter to improve image quality. Following the pre-processing color-based segmentation (RGB Thresholding) is utilized for the segmentation process. Next, the Feature extraction is conducted using a pretrained neural network, such as VGG-19. Subsequently, the extracted features are fed into a classification model like Random Forest (RF) to distinguish between different mango fruit diseases. A comprehensive analysis of experimental results indicates that the CONV-RFDNN model surpasses recent approaches, exhibiting superior performance in the detection and classification of mango fruit diseases.

The structure of the paper unfolds as follows: In Section 1, we introduce the project. Section 2 offers a brief overview of the conducted literature survey. Moving on to Section 3, we detail the operational procedures of the proposed system

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and delve into its execution. The ensuing Section 4 outlines the conclusions drawn and the outcomes achieved. Finally, Section 5 serves as a conclusion, summarizing our findings and exploring potential directions for future research.

2. Related Works

This section is given to the review of research on images associated with image categorization, identifying fruits, sorting, and diagnosing illnesses. The prevailing approach in research on fruit identification and disease detection involves the utilization of color and texture for categorization. Notably, a significant portion of fruit identification studies concentrates on tree-based fruits, while the present research specifically addresses methods for classifying fruit varieties. The existing literature predominantly emphasizes research on fruit disease detection, limiting exploration in this particular domain. Within this section, various research methods are discussed to provide insights into the latest developments in the topics covered in this study.

In [7], a mix of the Convolutional Neural Network (CNN) process for extracting features and the Histogram of Oriented Gradients method for capturing shape and texture details is utilized. The obtained characteristics are then fed into a disease classification model to efficiently recognize different diseases. Empirical proof backs the effectiveness of this suggested method, showing outstanding precision in the identification and grouping of illnesses. Significantly, the performance of the hybrid CNN-HOG model outperforms that of individual CNN or HOG methods, showcasing the collaborative essence of these two approaches in the realm of mango disease detection and classification. In [8], a distinct path is chosen, incorporating a cost-effective Vector Network Analyzer tool. This strategy is bolstered by integrating both the K-nearest neighbor algorithm and a Neural Network design. In [9], an innovative strategy is advised for predicting artificially ripened mango fruits using a CNN. The proposed technique involves applying binary cross-entropy to decrease loss during the forecasting step.

In [10], a CNN is utilized for categorizing four fruit varieties – Banana, Papaya, Mango, and Guava – based on their ripeness stages: unripe, ripe, and excessively ripe. The design utilizes a dataset of local fruits to assess their life cycle across different developmental stages. In [11] a recent publication, a novel approach to image-utilizing light CNNs was introduced in the context of enhancing the checkout process efficiency within retail establishments. The research work introduces a dataset containing three distinct fruit categories: items enclosed in plastic bags, unpackaged items, and those falling outside these categories. The proposed CNN model integrates various input features, including an individual RGB color, histogram, and centroid derived from K-means clustering to elevate the classification precision. Another study [12] explored the utilization of the color_moment feature extraction technique to compute statistical characteristics (mean and standard deviation) across the RGB color channels. This method also incorporates binarized representations for attributes linked to the physical structure. A comprehensive feature vector encompassing color moments and shape attributes is subsequently constructed to aid in the classification process. Moving forward, there is a particular interest in [13] automating the classification of mangoes to assess their quality pre-shipment to the market. This research endeavor focuses on conceptualizing, designing, and materializing a mango sorting model. Furthermore, the study highlights the integration of image processing technologies with artificial intelligence to develop an automated mango classification mechanism.

3. Proposed CONV-RFDNN Approach

The CONV-RFDNN approach adheres to a detailed workflow, illustrated in Fig 1. Initially, a Gaussian filter is applied for noise removal, enhancing image quality. Following this, Color-based segmentation (RGB Thresholding) is utilized for the segmentation process. Subsequently, the VGG-19 model is employed to extract features, and ultimately, the Random Forest is utilized for image classification, assigning distinct class labels. Further details for each stage are provided in the following sections.

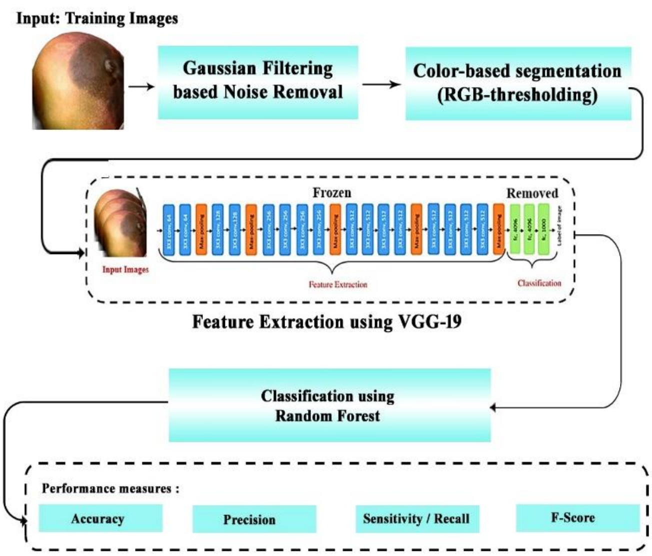

Fig. 1 Overall Architecture of the Proposed CONV-RFDNN model

3.1. Gaussian filter-based noise removal

Gaussian filtering is a commonly used method for noise reduction in images, including diseased mango fruit images. The Gaussian filter operates by smoothing the image while preserving edges, and it is particularly effective at reducing high-frequency noise. Here's how the Gaussian filter helps remove noise, along with the formula:

The 2D Gaussian filter is expressed as:

$$G(x,y) = \frac{1}{2\pi\sigma^2}.\ e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Where:

G(x,y) is the Gaussian kernel.

(x,y) are the spatial coordinates.

σ is the standard deviation, controlling the spread of the Gaussian distribution.

The Gaussian filter is applied to the image using convolution. For each pixel in the image, the filter calculates a weighted average of its neighboring pixels, giving more weight to pixels closer to the center and less weight to those farther away [14].

$$I'(x,y) = \sum_{i=-\infty}^{\infty}\sum_{j=-\infty}^{\infty} I(x+i,y+j).G(i,j) \quad (2)$$

Where:

I′ (x,y) is the filtered pixel value.

I(x+i,y+j) are the neighboring pixel values.

G(i,j) is the Gaussian kernel.

The Gaussian filter brings about a smoothing effect by assigning higher weights to pixels close by and lower weights to those located farther away. This aids in blurring out high-frequency noise in the image while preserving crucial structural information. Rapid changes in pixel intensity typically represent high-frequency noise. The Gaussian filter reduces the impact of such noise by smoothing out these rapid changes. The Gaussian filter is designed to preserve edges by gradually decreasing weights with distance. This ensures that the filter does not overly blur regions with significant intensity variations, maintaining the overall structure of the mango fruit and its diseased areas as shown in Fig 2. The choice of σ influences the amount of smoothing applied. A higher σ results in more extensive smoothing, while a lower σ retains more fine details. Adjusting σ is crucial to balancing noise reduction with preserving important image features.

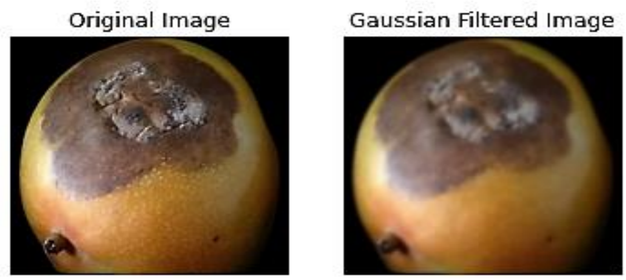

Fig 2. Gaussian Filter based noise removed images

3.2. Color-based Segmentation (RGB Thresholding)

RGB threshold-based segmentation plays a crucial role in mango fruit disease detection and classification tasks by helping to isolate regions of interest associated with diseased areas. Mango diseases often manifest as changes in color, texture, or both. RGB thresholding enables the identification of specific color ranges associated with diseased areas, allowing for discrimination between healthy and diseased regions. By setting appropriate threshold values for the red, green, and blue channels, the image can be segmented and regions likely to contain diseased portions of the mango as shown in Fig 3. This helps in focusing the analysis on relevant areas and reduces computational complexity. Thresholding aids in isolating diseased regions, making it easier to extract meaningful features for subsequent analysis. Features such as color histograms, texture patterns, or shape characteristics can be extracted from these segmented regions, forming the basis for disease classification. RGB thresholding enhances the accuracy of disease detection by concentrating on the specific color characteristics associated with diseases [15]. This approach is effective when diseases exhibit distinct color variations compared to the healthy portions of the mango fruit. RGB thresholding is a relatively simple and computationally efficient method, making it suitable for real-time or near-real-time applications. It provides a quick initial step in the image processing pipeline before more complex algorithms are applied for further analysis. Threshold values can be adjusted based on the characteristics of different diseases and variations in lighting conditions. This adaptability makes RGB thresholding a versatile technique that can be fine-tuned for specific disease-detection tasks. RGB thresholding serves as a pre-processing step in the image analysis pipeline. It helps in reducing noise and irrelevant information, making the subsequent stages of feature extraction and classification more robust and efficient.

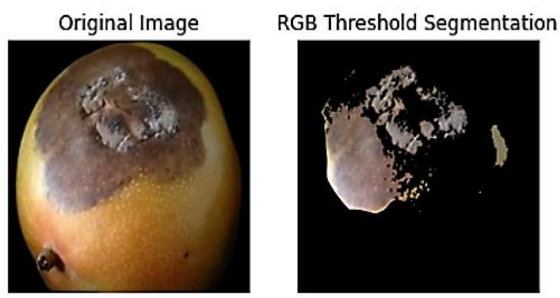

Fig 3. RGB Threshold based segmented images

3.2. VGG-19-based Feature Extraction

VGG-19 (Visual Geometry Group 19-layer) is a deep convolutional neural network architecture that has proven effective for image classification tasks. In the situation of mango fruit disease detection and classification tasks, having recourse to VGG-19 for feature extraction may present various advantages. VGG-19 is a deep architecture with 19 layers, allowing it to learn hierarchical features from the input images. The initial layers capture low-level features like edges and textures, while deeper layers extract more complex and abstract features. This hierarchical representation is valuable for capturing the diverse characteristics of mango diseases. VGG-19, pre-trained on large-scale image datasets, can be utilized as a feature extractor for mango fruit disease images. Transfer learning enables the model to leverage knowledge gained from the pre-training task, leading to better generalization and improved performance on the disease detection task, even when the available dataset for mango diseases is limited. The deep layers of VGG-19 can learn discriminative features that are relevant for distinguishing between different classes of mango diseases [16]. These features may include color patterns, texture variations, and other complex structures associated with specific diseases. The fully connected layers at the end of VGG-19 act as a feature vector that summarizes the high-level representations learned by the convolutional layers. This reduces the dimensionality of the data, making it more manageable for subsequent classification tasks. Mango fruit diseases can exhibit diverse visual symptoms. VGG-19's ability to learn a wide range of features makes it adaptable to different diseases, allowing the model to capture common and subtle visual cues associated with various diseases. The pre-trained VGG-19 model can be fine-tuned on a specific mango disease dataset. Fine-tuning allows the model to specialize in recognizing features relevant to mango diseases while retaining the knowledge gained from the pre-training on generic image datasets. VGG-19 has demonstrated robustness to variations in lighting conditions, image quality, and background clutter. This robustness is advantageous when working with diverse mango fruit images captured in different environments. In the conducted study, the upper layers of the VGG-19 convolutional neural network were frozen during the training process as depicted in Fig 4. This implies that these layers, responsible for high-level feature extraction, were kept fixed and not updated during training. The primary utilization of the frozen VGG-19 was solely to extract meaningful features from the input data rather than fine-tune the entire model.

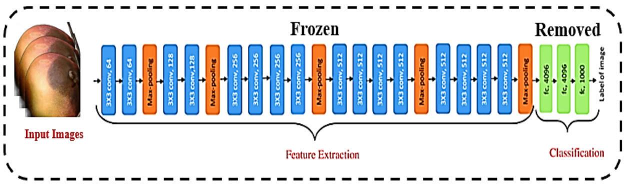

Fig 4. VGG-19 as a feature extractor

3.4. Classification using Random Forest

Random Forest emerges as a pivotal machine learning algorithm in the realm of mango fruit disease detection and classification. Serving as an ensemble learning method, Random Forest amalgamates insights from multiple decision trees to formulate predictions, employing a voting mechanism to reach a final decision. This approach enhances the model's robustness and generalization, which is crucial for accurate mango disease classification. In the context of mango fruit disease classification, intricate relationships and interactions among various features in images demand a versatile algorithm. Random Forest excels in capturing complex non-linear connections between input features and output classes. Its adaptability to diverse input features makes it well-suited for scenarios where distinct aspects of mango fruit images contribute to the classification task [17]. Additionally, Random Forest provides valuable insights through a measure of feature importance, revealing the contribution of each feature in the classification process. Understanding which features, such as color patterns and texture details, play a crucial role in distinguishing between healthy, infected, and fungal-diseased mango fruits is essential for diagnostic insights. Random Forest's inherent robustness to overfitting is particularly advantageous in diseased image classification tasks, ensuring that the model learns meaningful patterns rather than noise. This robustness contributes to the model's ability to generalize to new, unseen data, bolstering reliable mango disease detection. Diseased fruit image datasets, including those related to mango fruit diseases, often exhibit class imbalance. Random Forest adeptly handles imbalanced datasets, ensuring reliable predictions across different disease classes as depicted in Fig 5. Its capability to provide accurate predictions in scenarios where certain diseases may be less prevalent is a valuable asset for mango disease classification. The decision trees within the ensemble can be visualized, offering transparency into the decision-making process. This interpretability fosters trust among stakeholders, enabling better understanding and acceptance of the model's predictions by professionals involved in mango disease detection and classification.

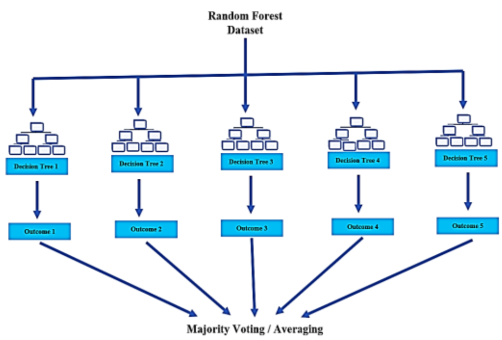

Fig 4. VGG-19 as a feature extractor

4. Performance Appraisal

4.1. Implementation Setup

In this section, experimental validation was conducted for the CONV-RFDNN method for detecting and classifying mango fruit diseases using diseased mango fruit images, taking into account various factors. The experiments were implemented using Python 3.6.5 on a computer equipped with an i5-8600K processor, 250GB SSD, GeForce 1050Ti 4GB GPU, 16GB RAM, and a 1TB HDD. The performance assessment of the CONV-RFDNN model involved key metrics such as Sensitivity, Specificity, Precision, Accuracy, and F-score. The validation utilized a benchmark Kaggle dataset containing diseased mango fruit images [18]. Sample test images representing each class are depicted in Fig 6, and the corresponding number of samples is provided in Table 1.

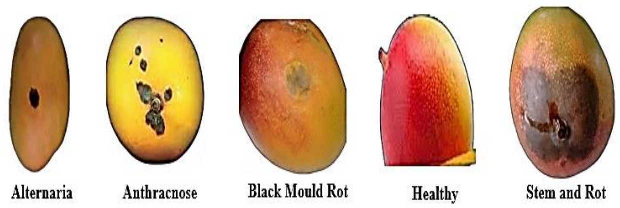

Fig 6. Sample Images

Table 1. Dataset Description

Class	Number of Samples
Alternaria	165
Anthracnose	129
Black Mould Rot	182
Healthy	205
Stem and Rot	157
Total	**838**

4.2. Observations and Discussion

In Fig. 7, the confusion matrix along the precision-recall & ROC curve showcases the accurate classifications of the CONV-RFDNN model across different classes during its execution for mango fruit disease detection and classification. The efficiency analysis of the CONV-RFDNN model, as depicted in Table 2 and Fig. 8, underscores its effectiveness in classifying mango fruit images for disease detection on training and testing datasets. In this case, a split of 70% for training and 30% for testing is employed. Remarkably, the model demonstrates exceptional performance in identifying mango fruit diseases, achieving higher performance measures. It attains an F-score of 96.00%, an impressive overall accuracy of 97.00%, Sensitivity of 98.00% and a precision of 96.00%.

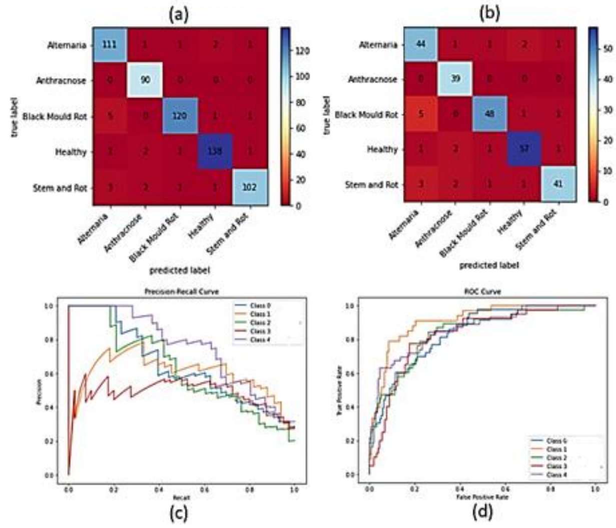

Fig. 7. (a) Confusion Matrix based on TR set (b) Confusion Matrix based on TS set (c) Precision-Recall Curve (d) ROC Curve

Table 2. Results of CONV-RFDNN used for mango fruit disease classification

Network	Accuracy (%)	Sensitivity / Recall (%)	Precision (%)	F-Score (%)
CONV-RFDNN	97	98	96	96

A detailed comparison analysis in Table 3 is conducted to showcase the superior performance of the proposed CONV-RFDNN model. The table outlines a concise evaluation of Accuracy and other parameters for the CONV-RFDNN in comparison to existing studies. Table 3 indicated that the accuracy values of the [19] models were the lowest at 95.00%, 82.00%, 86.00%, and 97.00% respectively. While the Recall values of the [19] models demonstrated lower percentages ranging from 82.00% to 94.03%, the proposed model surpassed them with an accuracy of 98.00%. The precision values of the [19] models were notably minimal, ranging from 92.00% to 95.00%, whereas the proposed model excelled with a higher precision of 96.00%. Furthermore, the F1-score evaluation of the CONV-RFDNN model presented in Table 3 showcased that the [19] models exhibited lower F-score values, ranging from 68.00% to 94.02%. In contrast, the proposed CONV-RFDNN model displayed optimal performance with a higher F-score of 96.00%. A visual representation of the comprehensive analysis comparing the proposed model with existing models is depicted in Fig. 9.model with existing models is depicted in Fig. 9.

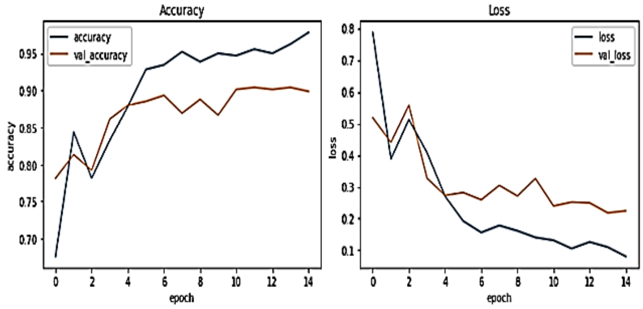

Fig. 8. Accuracy & Loss graph based on Training and Testing set

Table 3. Assessment of the Proposed Strategy in Comparison to Existing Approaches

Models	Accuracy (%)	Sensitivity / Recall (%)	Precision (%)	F – Score (%)
CNN-HOG	95.00	82.00	92.00	68.00
CNN	82.00	79.00	93.00	63.00
L-CNN	86.00	69.00	78.00	57.00
CNN-FOA	97.00	94.03	95.00	94.02
Proposed CONV-RFDNN	**98.00**	**98.00**	**96.00**	**96.00**

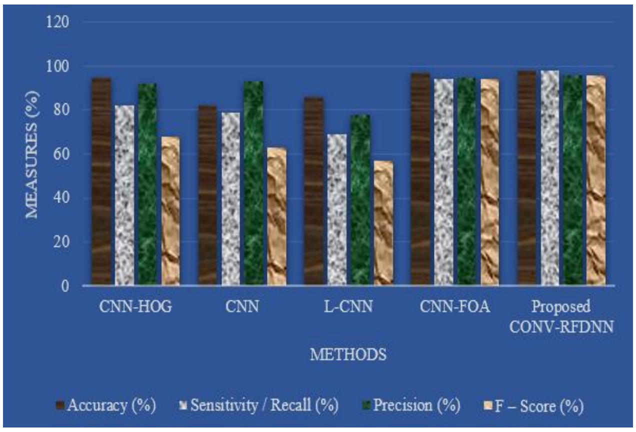

Fig. 9. Overall Comparative Analysis of the existing with proposed approach

5. Conclusion

The mango holds significant importance as an agricultural commodity traded globally. Traditional methods for assessing mango fruit quality involve manual inspection, requiring substantial time and labor investments, along with expertise. Unfortunately, this manual evaluation results in the destruction of sampled fruit, reducing overall output. To address these challenges, non-destructive methodologies, including inside inspection, have been developed. The proposed multi-disease categorization for mango fruits, as demonstrated in the experimental investigation, shows promising results. There is a pressing need for advancements in deploying comprehensive disease monitoring systems across various plant species and improving the practicality of the proposed methodologies. An objective of upcoming research will be to delve into fusion strategies for the extraction of crucial characteristics and the inclusion of more leaf samples in datasets.

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