IoT-based Freshness Detection and Deep Learning for Artificial Ripeness Identification

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Abstract— **Critical challenges in the fruit industry are addressed by the system, focusing on detecting chemically treated fruits and implementing real-time monitoring during transportation and storage. Through deep learning image processing, a model utilizing the Xception architecture has been developed, achieving high accuracy in distinguishing between chemically treated and untreated fruits. Trained on a diverse dataset and incorporating advanced image analysis techniques, this model enables the identification of subtle visual cues indicative of chemical treatment, ensuring food safety and quality. Concurrently, Internet of Things (IoT) sensors, including alcohol sensor (MQ-3 sensor), methane gas sensor (MQ-4 sensor), and Temperature and humidity sensor (DH11 sensor), are utilized by the system to monitor temperature, humidity, and gas emissions in real-time. Calibration processes ensure precise measurements, while remote access via the Blynk platform allows stakeholders to monitor fruit conditions and respond promptly to potential spoilage. Field testing has validated the effectiveness of the approach in reducing fruit waste and preserving optimal storage conditions throughout the supply chain. By combining machine learning and IoT technologies, a comprehensive solution is offered, enhancing food safety, quality assurance, and sustainability in the fruit industry.**

Keywords—fruit quality monitoring, chemical detection, deep learning, image processing, IoT sensors, real-time monitoring, food safety, supply chain, sustainability.

I. INTRODUCTION

Fruits are a great source of nutrients for humans. There is a large fruit industry worldwide, and many people take fruit as part of their diet. There are two major issues in the fruit industry. One is that many fruit producers and those associated with the fruit logistics process apply chemicals to the fruit for fastening and ripening; the resulting fruits are of poor quality and contain less nourishment. These chemicals are extremely harmful to human health [1][2]. Another major issue in the fruit sector is that many fruits have been destroyed throughout the logistics process. The cause of this issue is a lack of effective monitoring measures throughout the logistics chain, including transportation and storage. Temperature and humidity are also significant factors in deterioration during transportation and storage. It will also affect the fruit's shelf life [3][4]. Therefore, in order to guarantee both food quality and human health, these two factors must also be taken into consideration. It is essential that these two issues are resolved.

To deal with chemically treated fruits, an identification technique is necessary. Chemically added fruits have slight color and appearance alterations when compared to non-chemically treated fruits. However, the human eye cannot detect these changes. Deep learning image processing technology is capable of detecting these tiny changes. Consequently, a model for a deep learning classifier is introduced [5][6]. A large number of fruit images, both with and without chemical additions, were gathered [7]. This approach is used to classify data in a mobile application designed for users. The application allows anyone to easily detect fruits with chemical additives by simply snapping a picture of the fruit or uploading it to a mobile application [8][9]. A real-time fruit monitoring technique employing IoT sensors is offered to mitigate fruit deterioration throughout the logistic process [10][11]. This approach uses a temperature and humidity sensor to track the two factors: temperature and humidity [12][13]. When fruits spoil, they release methane gas and alcohol gas. It can be detected using the MQ-4 sensor and the MQ-3 sensor [14][15]. Autonomous humidifier and fan-based cooling systems have been developed to address low humidity and temperature concerns [16][17]. There is no need for humans to periodically check on fruits because this technology uses automatic real-time monitoring, an alerting system, and a mobile application to see the monitoring data[18][19]. These two approaches can improve fruit quality and decrease fruit waste, and chemical detection techniques can improve nutrition, safeguard human health, and reduce food fraud.

II. RELATED WORKS

The fruit industry is crucial for providing essential nutrients to global populations. However, challenges persist in ensuring fruit quality and safety, particularly concerning the detection of chemically treated fruits and real-time monitoring during transportation and storage. Recent advancements in analytical techniques, IoT-based monitoring systems, and machine learning approaches are reviewed herein, all relevant to addressing these challenges.

Recent research has focused on the development of advanced analytical methods for detecting chemical residues in fruits. In this study discussed the application of mass spectrometry and chromatography techniques for identifying and quantifying residual contaminants, ensuring compliance with safety regulations [5]. These methods provide reliable means of assessing fruit quality and safety by analyzing chemical composition.

IoT-based monitoring systems have emerged as valuable tools for real-time monitoring of fruit quality during transportation and storage. In this study highlighted the integration of wireless connectivity and sensor networks to track crucial parameters such as temperature, humidity, and gas emissions [6]. These systems enable stakeholders to remotely access and analyze data, facilitating timely interventions to mitigate quality degradation.

Machine learning approaches offer automated solutions for classifying fruit ripeness based on multi-modal sensor data. In this study discussed the application of convolutional neural networks (CNNs) and support vector machines (SVMs) for identifying subtle cues indicative of fruit ripeness, facilitating efficient quality assessment [7]. These algorithms enable accurate and automated classification of fruit ripeness, enhancing quality control measures.

Chemometric methods have been utilized to assess fruit quality based on chemical composition data. In this study reviewed the application of multivariate analysis techniques such as principal component analysis (PCA) and partial least squares regression (PLSR) for comprehensive evaluation of fruit characteristics [8]. These methods enable objective assessment of fruit quality, aiding in quality assurance and decision-making processes.

III. METHODOLAGY

In two primary areas, coverage is provided by the system: first, food quality monitoring using IoT; and second, the detection of artificially ripened fruits using machine learning.

1. DETECTION OF ARTIFICIALLY RIPENED FRUITS USING MACHINE LEARNING.

A. IMPLEMENTATION

Image Processing has a wide range of real-time applications in almost every field due to its ability to provide more accurate, consistent, and faster results than any other technique. The following steps illustrate the model(Refer to figure 1).

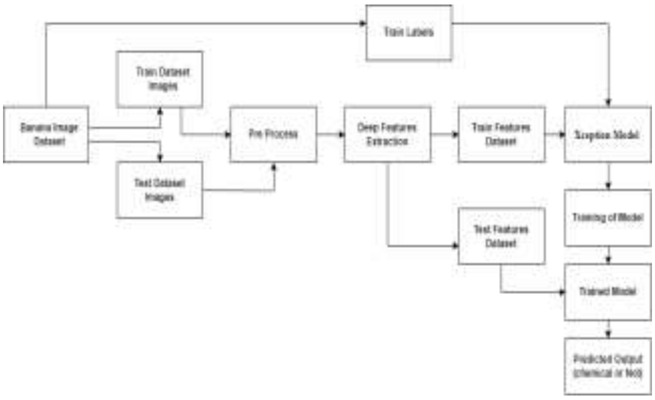

Figure 1: methodology of the system

B. MODEL ARCHITECTURE

A model architecture has been created that accurately captures the elements allowing for differentiation in banana photos, facilitating accurate categorization. Pre-trained on the ImageNet dataset, the Xception model was employed as the foundational architecture. The decision was driven by Xception's shown ability to handle picture categorization tasks well. Further layers, including dense layers with rectified linear unit (ReLU) activation functions, were added to the pre-trained model in order to modify it for the particular objective. The model can predict the chemical condition of the banana and learn high-level abstractions from the input photos thanks to these layers.

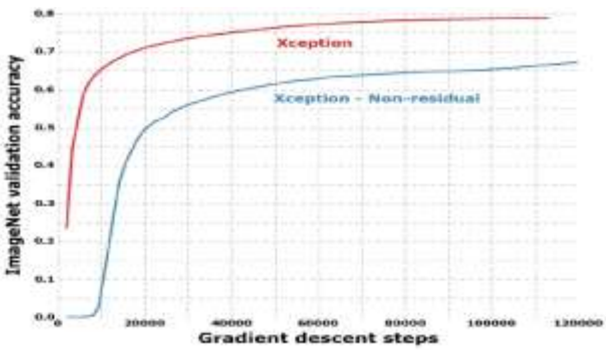

Figure 2: ImageNet: Validation Accuracy Against Gradient Descent Steps

C. DATA COLLECTION AND PREPROCESSING

The caliber and diversity of the training dataset are critical to the performance of the model. A large dataset was gathered from multiple sources, comprising 990 photos of bananas. The photographs in this collection were carefully chosen to provide a fair portrayal of both chemical and organic bananas. Data preprocessing methods, including downsizing and standardization, were used to increase the dataset's heterogeneity and enhance model generalization. In order to strengthen the training dataset, additional techniques for data augmentation were used, such as random flipping, rotation, and zooming.

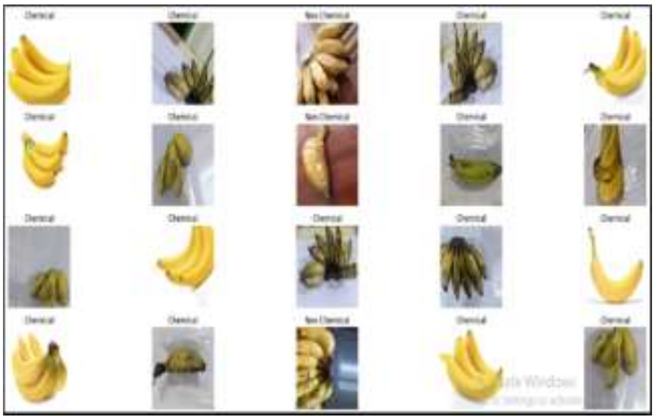

Figure 3: Sample images of dataset

D. TRAINING AND AVALUATION

To train the model, adjustments were carefully made to the pre-trained Xception model using the enhanced dataset. Performance indicators, including accuracy and loss, were closely monitored throughout the training process. To guarantee the model's efficacy, the parameters such as batch size and number of epochs were improved.

Binary accuracy, recall, and precision were used to thoroughly assess the model's performance after training. With the use of these metrics, the evaluation of how well the model distinguished between chemical and non-chemical bananas was conducted.

The model performed exceptionally well in the last epoch (Epoch 5/5). On the training dataset, it obtained an accuracy of 99.34% and a loss of 0.0292. The model obtained a loss of 0.0465 and an accuracy of 96.97% on the validation dataset. These findings demonstrate the model's resilience in correctly identifying bananas as chemical or non-chemical.

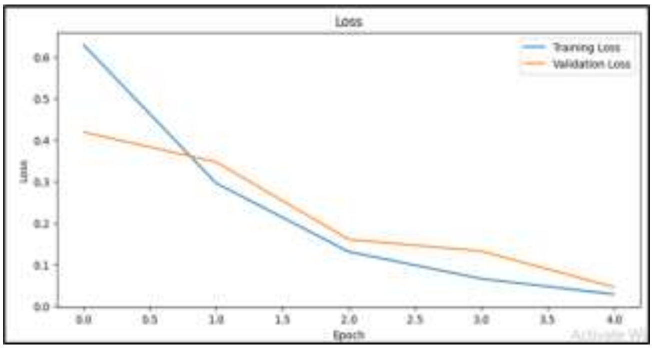

Figure 4: Training and validation Loss

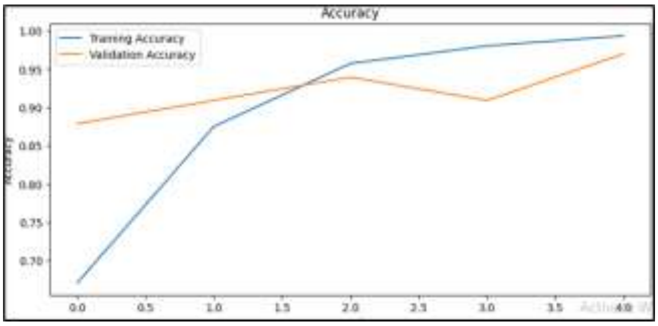

Figure 5:Training and validation Accuracy

E. OUTCOMES

The outcomes of the experiments demonstrate how well the suggested model works to identify healthy bananas. High accuracy, precision, and recall rates were among the model's remarkable performance indicators. The aforementioned findings highlight the model's precision in distinguishing between chemical and non-chemical bananas, hence tackling the crucial requirement of evaluating quality in the banana sector. A thorough examination and explanation of the findings are offered, addressing the variables that affect the model's performance and possible directions for development.

A visual comparison of the Red, Green, Blue (RGB) histograms of two photos of bananas one labeled as chemical and the other as non-chemical is made possible by the function plot RGB histogram comparison. The purpose of this comparison is to draw attention to any potential variations in the two varieties of bananas' color distribution and intensity.

Plotting the individual histograms for the red, green, and blue RGB channels enables a thorough examination of color composition. This program allows users to identify any discernible differences in color distribution between the chemical and non-chemical banana histograms.

This visualization can be very useful for spotting minute differences in banana appearance that might point to chemical processing. Changes in color intensity or peaks in particular color channels, for example, can indicate variations in ripeness or the presence of chemical residues. By making better use of this feature, stakeholders may decide on the safety and quality of bananas, ultimately improving consumer confidence in the produce market and public health.

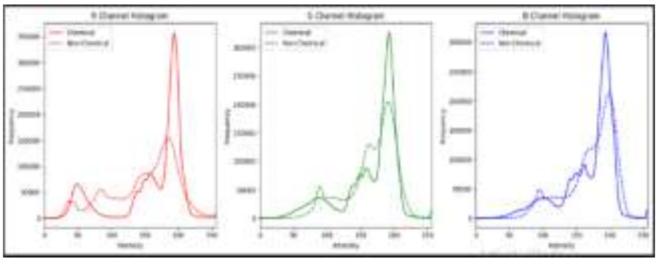

Figure 6: Plot RGB histogram comparison for chemical and non-chemical bananas

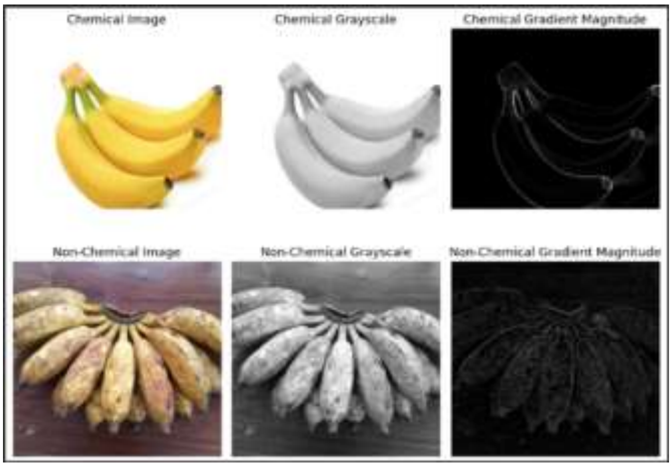

Figure 7: Differences for chemical and non-chemical banana classification

F. DEVELOPING AN ANDROID APP FOR DETECTING ARTIFICIALLY RIPENED

In addition to the model creation, an Android application was developed to facilitate real-time inspection of bananas. The trained model is smoothly integrated into the application, enabling users to capture banana images with their cellphones and receive immediate chemical status feedback. The application's features and functionalities, including the integration of image processing methods and the design of the user interface, are discussed. The idea is put into practice through the Android application, enhancing accessibility for customers and other supply chain participants.

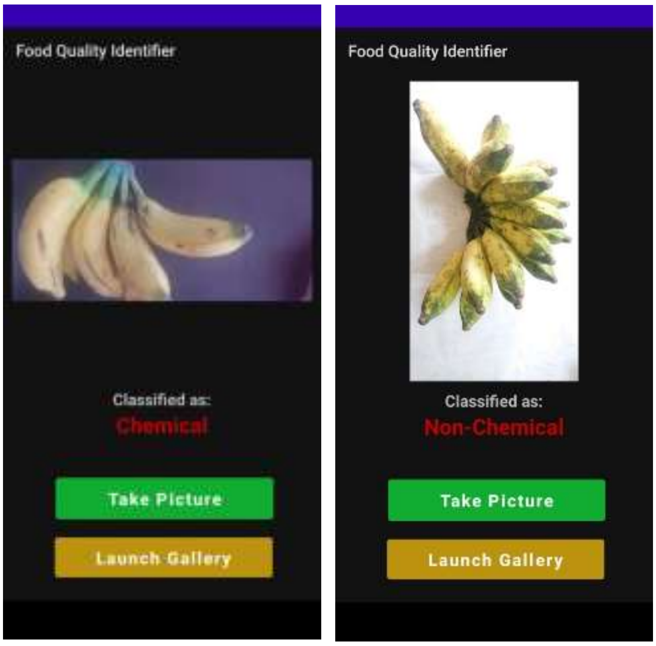

Figure 8: Screenshots of the android application

G. CONCLUTION AND FUTURE DIRECTIONS

A novel method has been introduced that utilizes deep learning and sophisticated image-processing techniques to identify healthy bananas. When combined with the Android application, the model provides a promising solution to the problems related to evaluating banana quality. The findings of the study demonstrate the effectiveness of the strategy and its potential impact on the market's availability of safe, high-quality bananas. Several directions for future research are envisioned, including the investigation of multi-modal data fusion and the addition of more capabilities to the Android application for stakeholders.

2 FOOD QUALITY MONITORING USING IOT

A. IMPLEMENTATION

The use of an IoT-based smart device presents a viable answer to the problem of fruit waste in the agriculture sector [9]. This device uses data analytics and sensor technologies to track fruit conditions in real-time as it's being transported and stored. Stakeholders can preserve fruit quality and freshness by identifying any threats and acting quickly to address them by utilizing networking solutions. This strategy improves the sustainability, efficiency, and transparency of the supply chain, which eventually reduces losses and maximizes resource use in the agriculture industry.

B. METHODOLOGY

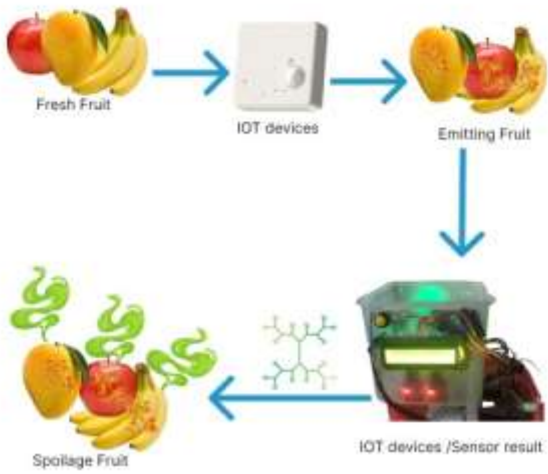

Figure 9: Process of food monitoring

I. Description of the Smart IoT Device and Its Components

To efficiently monitor and reduce fruit waste during storage and transportation, the IoT smart device is made up of multiple crucial parts. As the device's brain, the ESP32 module is the main component. It is a multipurpose microcontroller. Because of its great processing capability, integrated Wireless Fidelity (Wi-Fi) and Bluetooth, and low power consumption, the ESP32 module is the perfect choice for Internet of Things applications [10].

Other essential sensors for fruit condition monitoring complete the ESP32 module. These comprise the MQ-3 sensor and MQ-4 sensor, which identify gasses released by rotten or broken fruits. Since they can reliably and sensitively identify even minute levels of gases that are suggestive of spoiled fruit, these sensors have been carefully chosen. To ensure that fruits are stored in the best possible conditions, the gadget also includes an embedded DH11 sensor to track ambient humidity levels.

Because these sensors are integrated into the smart device, it is possible to monitor important fruit quality characteristics in real time. This gives stakeholders practical information that they can use to reduce waste and stop spoiling along the chain.
them

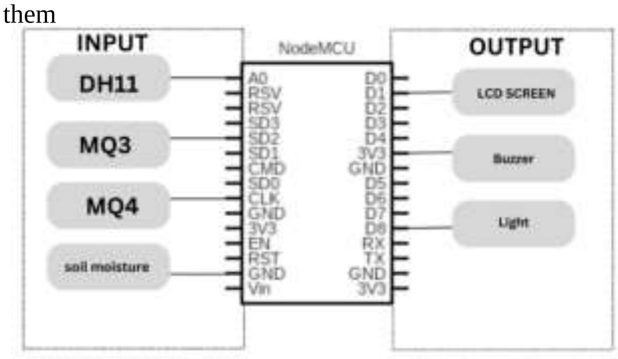

Figure 10: components of IOT device

II. Interpretation of the Gas and Humidity Level Calibration Process

Setting up the smart device for calibration is essential to guaranteeing precise gas and humidity detection and measurement. Thorough calibration is applied to every sensor in order to create a reference point for precise measurements.

In a controlled setting, calibration for gas sensors, like the MQ4 sensor and MQ3 sensor, entails exposing the sensors to known gas concentrations. This procedure guarantees that even minute amounts of gases released by rotten fruits can be precisely detected by the gadget and enables sensitivity modification of the sensor.

To connect its measurements with established humidity levels, the DH11 sensor also goes through calibration. To provide accurate and consistent observations, this calibration procedure takes into consideration environmental variables such changes in humidity and temperature.

The intelligent device provides accurate and trustworthy data on the state of the fruit by calibrating its sensors. This will help stakeholders make well-informed decisions that will successfully reduce waste.

Figure 11: Image of humidity level

Figure 12: Image of temperature level

III. Configuration of the ESP32 Module for Real-Time Data Display and Remote Access via the Blynk Platform

Configured to enable remote access to sensor readings through the Blynk platform and real-time data display, the ESP32 module displays data. Creating personalized dashboards and interfaces for tracking and managing IoT devices is possible with Blynk, an intuitive IoT platform.

Stakeholders get real-time access to sensor data via the Blynk platform, including humidity levels, gas concentrations, and any alarms the device may have caused. Via Wi-Fi connectivity between the ESP32 module and the Blynk server, sensor readings can be easily accessed remotely from any location with an internet connection.

In order to prevent spoiling and reduce wastage in the supply chain, the ESP32 module and Blynk platform setup offer stakeholders an easy-to-use interface for tracking fruit condition and taking prompt action.

IV. Conduct of Field Tests to Evaluate the Device's Performance in Various Transportation and Storage Conditions

Field tests are carried out to evaluate the smart device's performance in the real world by simulating different types of transportation and storage conditions that are frequently encountered in the supply chain for agriculture.

A variety of environmental factors, including variations in temperature, humidity, and physical disturbance mimicking transit, are applied to different fruit kinds. Through the course of these tests, the smart device continuously checks the condition of the fruit, giving stakeholders real-time data on how well the device detects and mitigates rotting.

In order to pinpoint areas where the device's functioning and design need to be improved, input from stakeholders' farmers, distributors, and store managers is gathered during the field tests.

The effectiveness of the smart device in mitigating fruit waste issues in various supply chain scenarios is assessed through field testing, which shapes future improvements for the gadget's useful application in the farming industry.

Figure 13: Image of temperature level

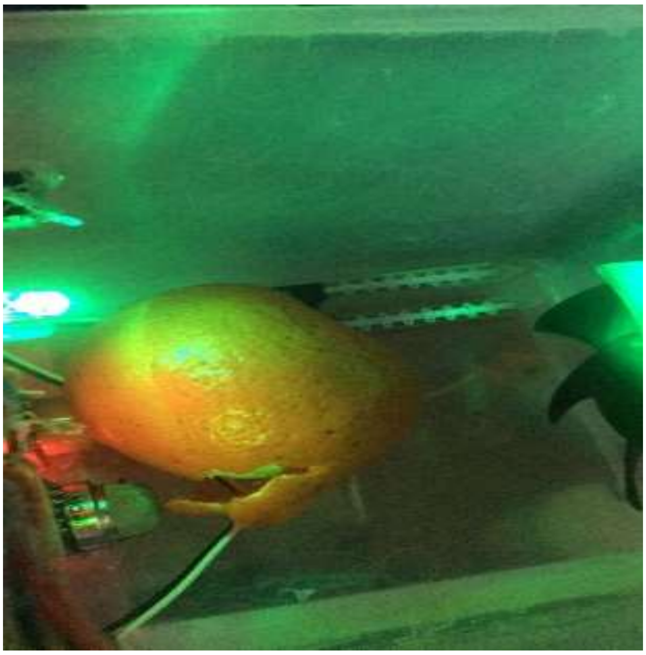

Figure 14: Testing the device using an orange fruit

C. *RESULT ANALYSIS*

The outcomes of the experiments underscore the efficacy of the model in discerning healthy bananas, exhibiting high accuracy, precision, and recall rates. This precision is vital for evaluating banana quality, particularly in distinguishing between chemical and non-chemical bananas. Through thorough examination and explanation, variables affecting model performance are addressed, and directions for development are proposed. Visualizing the Red, Green, Blue (RGB) histograms of banana photos aids in identifying subtle color variations, potentially indicating chemical processing. Such insights are crucial for stakeholders in ensuring banana safety and quality, bolstering consumer confidence. Moreover, the Android application seamlessly integrates the model, empowering users to capture banana images for instant chemical status feedback, enhancing accessibility and real-time inspection.

Field testing validates the device's ability to detect spoilage and maintain ideal storage conditions, while stakeholder feedback informs iterative improvements, emphasizing the collaborative process in fostering innovation and enhancing the device's feasibility for widespread adoption in agricultural settings.

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