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REAL-TIME TOMATO LEAF DISEASE CLASSIFICATION AND TREATMENT RECOMMENDATION USING DEEP LEARNING TECHNIQUES

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Abstract: Tomato plants are vulnerable to numerous fungal, bacterial, and viral diseases that severely impact crop yield and farm productivity. Early and accurate disease identification is essential to prevent spread and reduce economic losses. Traditional manual inspection methods are time-consuming and impractical at scale, highlighting the need for automated solutions. This research presents a real-time tomato leaf disease classification and treatment recommendation system using deep learning. Four architectures are evaluated comparatively: CNN, MobileNetV2, ResNet50, and EfficientNetB0. EfficientNetB0 achieves the highest classification accuracy and is deployed for live webcam-based inference. A rule-based recommendation module delivers disease-specific guidance covering chemical, organic, and preventive management strategies. The integrated system provides farmers with a reliable, end-to-end decision-support tool for early diagnosis and effective crop management.

Keywords: Tomato Leaf Disease Detection, Deep Learning, Transfer Learning, Convolutional Neural Networks (CNN), MobileNetV2, ResNet50, EfficientNetB0, Real-Time Disease Classification, Treatment Recommendation System, Precision Agriculture.

I. INTRODUCTION

Agriculture plays a vital role in sustaining the global economy and ensuring food security, with tomato being one of the most widely cultivated and economically important vegetable crops. However, tomato plants are highly susceptible to a wide range of fungal, bacterial, and viral infections that adversely affect crop yield, quality, and overall agricultural productivity. Diseases such as early blight, late blight, bacterial spot, and viral infections can spread rapidly if not detected at an early stage, leading to significant economic losses for farmers.

Early detection and accurate identification of plant diseases are essential to control their spread and implement effective treatment strategies. Conventional methods of disease diagnosis rely on manual inspection by farmers or agricultural experts. These approaches are not only time-consuming but also require domain expertise, which is often unavailable in rural and remote farming areas. As a result, delayed or incorrect diagnosis may lead to improper treatment, further worsening crop damage.

Recent advances in computer vision and deep learning have created new opportunities for automated plant disease detection [26][40]. Convolutional Neural Networks (CNNs) have proven particularly effective at extracting hierarchical features from raw image data and achieving competitive accuracy across diverse visual classification tasks [39]. Transfer learning adapting representations learned on large-scale datasets to domain-specific problems has further accelerated progress by reducing both training time and data requirements, with models such as MobileNetV2 [43], ResNet50 [44], and EfficientNetB0 [45] consistently outperforming networks trained from scratch.

Despite these advancements, many existing systems focus primarily on disease classification and lack real-time applicability and practical support for farmers. In addition, limited attention has been given to comparing multiple deep learning models to identify the most efficient architecture for real-world deployment. Moreover, most systems do not provide actionable treatment recommendations after disease detection, which is a critical requirement for effective crop management.

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To address these limitations, this research presents an end-to-end tomato leaf disease detection and treatment recommendation system grounded in deep learning [41]. A systematic multi-model comparison is conducted across CNN, MobileNetV2 [43], ResNet50 [44], and EfficientNetB0 [45] to evaluate classification accuracy and computational cost. EfficientNetB0 is selected for live deployment based on its superior experimental performance and compound-scaling efficiency [45]. Field-captured images from a mobile camera enable inference under realistic agricultural conditions, and a rule-based treatment recommendation module following the knowledge-base design described in [47] supplies disease-specific guidance covering chemical, biological, and cultural management options.

Together, these contributions advance the state of precision agriculture by coupling high-accuracy automated diagnosis with interpretable, field-ready treatment output bridging the gap between laboratory deep learning performance and on-farm usability.

II. PROBLEM STATEMENT

The tomato leaf diseases are often not detected in the early stages due to the unavailability of automated disease detection systems. The farmers often rely on their own knowledge and manual inspection to detect diseases in plants, which may lead to late detection and incorrect diagnosis of diseases. This leads to the rapid spread of the diseases, resulting in a substantial reduction in the yield of crops.

The major problems that are solved in this research work are:
• Late detection of tomato leaf diseases in the early stages of infection
• Manual inspection and unavailability of agricultural experts
• Unavailability of automated real-time disease detection systems
• Unavailability of comparative analysis of various deep learning models for accurate detection
• Unavailability of treatment recommendation systems after disease detection
The above problems emphasize the need for an intelligent automated system that can detect tomato leaf diseases in real-time, carry out multi-model deep learning analysis, and provide treatment recommendations for the identified diseases.

III. PROPOSED WORK

The proposed system presents a real-time tomato leaf disease classification and treatment recommendation framework using deep learning techniques. The system is designed to automatically detect diseases from tomato leaf images and provide appropriate treatment suggestions, enabling early intervention and efficient crop management. The entire workflow is implemented based on the developed code modules, including dataset loading, multi-model training, evaluation, and real-time deployment.

The system is capable of recognizing tomato leaf diseases using trained deep learning models and generating treatment recommendations based on the predicted disease class. The solution is fully deployable in real-time agricultural environments using camera-based input, making it a practical decision-support system for farmers.

The proposed system involves the following major steps:

- Image Acquisition
- Image Preprocessing
- Data Augmentation
- Deep learning-based disease classification
- Model evaluation and comparison
- Treatment recommendation and real-time inference

3.1 System Overview

The proposed architecture is structured as a unified, end-to-end pipeline incorporating four deep learning classifiers CNN, MobileNetV2 [43], ResNet50 [44], and EfficientNetB0 [45] trained on the PlantVillage benchmark [47]. A key distinction from prior single-model studies [3][4] is the addition of a deterministic treatment recommendation engine that translates each predicted disease label into structured agronomic guidance, giving farmers actionable output rather than a bare classification result. The pipeline spans the complete workflow: dataset acquisition, image preprocessing, parallel model training, cross-model benchmarking, and finally live deployment using EfficientNetB0.

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Raw tomato leaf images are drawn from the PlantVillage repository and supplemented with live camera feeds. Prior to training, each image is spatially normalized and pixel-scaled to establish a consistent input distribution across the dataset. Stochastic augmentation is then applied to artificially diversify the training pool and discourage model overfitting.

Preprocessed images are passed simultaneously through all four architectures. Transfer learning is leveraged to initialize weights from ImageNet-pretrained backbones, accelerating convergence and sharpening feature discrimination. Cross-model performance is assessed using accuracy, precision, recall, and F1-score to ensure a rigorous and unbiased comparison.

Benchmarking results identify EfficientNetB0 as the top-performing model across all evaluation metrics. Its trained weights are then integrated into a webcam inference loop, enabling frame-by-frame disease prediction with minimal latency.

Upon classification, each predicted label is routed to the recommendation engine, which retrieves the corresponding management protocol spanning chemical, organic, and cultural interventions from a structured knowledge base and renders it on-screen alongside the corresponding treatment suggestions to assist farmers in making timely decisions.

Overall, the proposed system functions as a scalable precision-agriculture tool that unifies automated multi-model disease diagnosis, real-time webcam inference, and knowledge-driven treatment guidance within a single deployable framework.

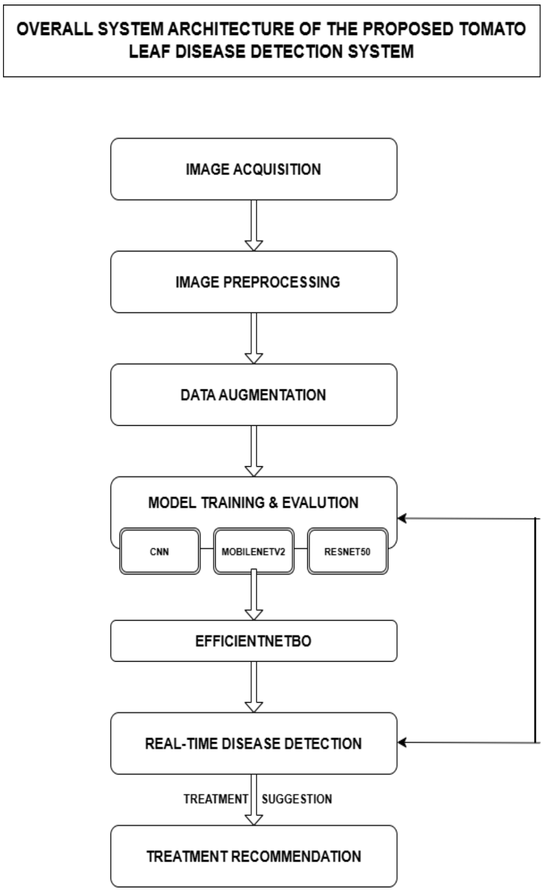

Figure-1: overall system architecture

3.2 Image Acquisition

Image collection forms the foundation of the proposed pipeline. Training data are sourced from the PlantVillage benchmark repository [47], which provides 14,529 annotated tomato leaf images spanning multiple disease categories and a healthy class. For real-time inference, images are captured directly via mobile cameras, webcams, or standard digital cameras, ensuring that the system can operate in field conditions without specialized equipment. Acquired images are forwarded to the preprocessing stage for further processing.

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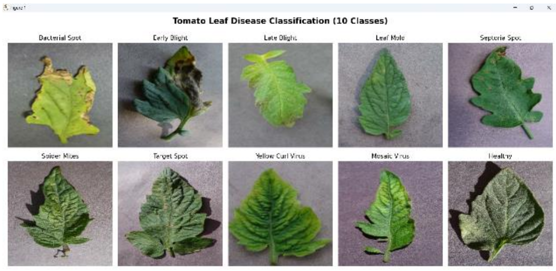

Image-1:sample image of tomato leaf diseases

3.3 Image Preprocessing
Each input image passes through a standardized preprocessing pipeline before being used for training. Following the methodology established in [41], all images are resized to 224 × 224 pixels to match the spatial input requirements of the selected architectures. Pixel intensities are subsequently normalized to the [0, 1] range to promote stable gradient updates during optimization. Where image acquisition conditions introduce noise, appropriate noise reduction techniques are applied to remove irrelevant artifacts prior to feature extraction.

3.4 Data Augmentation
To improve the generalization ability of the trained models and reduce the risk of overfitting, a set of standard augmentation transformations is applied to the training images following the approach described in [42]. The augmentation pipeline includes random rotation, horizontal and vertical flipping, zoom, scale variation, and brightness adjustment. These transformations artificially expand the effective size and diversity of the dataset, encouraging the models to learn disease-relevant features that remain consistent across varying lighting conditions, orientations, and imaging perspectives.

3.5 Disease Classification Using Deep Learning Models
The classification stage employs a structured multi-model evaluation protocol in which all four architectures are assessed under identical experimental conditions. Transfer learning is applied throughout pretrained ImageNet weights are loaded into each backbone and selectively fine-tuned on the tomato leaf dataset to exploit previously acquired visual representations and accelerate task-specific adaptation.

3.5.1 Convolutional Neural Network (CNN)
A custom-built CNN serves as the non-pretrained baseline in this work. The network accepts 224 × 224 × 3 RGB inputs and progressively deepens feature representations through three successive convolutional blocks with 32, 64, and 128 filters respectively, each paired with ReLU non-linearity and 2×2 max-pooling for spatial downsampling. The resulting feature maps are vectorized and routed through a 128-unit fully connected layer, regularized by a dropout layer (rate = 0.3) to mitigate overfitting, and terminated by a softmax head for multi-class probability estimation.

3.5.2 MobileNetV2
MobileNetV2 [43] is a computationally efficient architecture designed for deployment in resource-constrained, real-time settings. Its design relies on depthwise separable convolutions and inverted residual blocks with linear bottlenecks to substantially reduce parameter count and multiply-accumulate operations while preserving classification accuracy. In the proposed system, a pretrained MobileNetV2 backbone is adapted via transfer learning, with a global average pooling layer, a 128-neuron dense layer, a dropout layer (rate = 0.3), and a softmax output head appended for multi-class disease classification.

3.5.3 ResNet50
ResNet50 [44] is a 50-layer deep residual network whose identity shortcut connections allow gradients to propagate through very deep stacks without vanishing, enabling the training of significantly deeper architectures than previously practical. A pretrained ResNet50 backbone is fine-tuned using transfer learning, with a global average pooling layer, a 128-neuron dense layer, a dropout layer (0.3), and a softmax classifier added to adapt the model to tomato leaf disease recognition.

3.5.4 EfficientNetB0
EfficientNetB0 [45] applies a principled compound scaling strategy that simultaneously scales network depth, width, and input resolution using a fixed set of coefficients, yielding higher accuracy with fewer parameters than networks scaled along only one dimension. In the proposed system, a pretrained EfficientNetB0 backbone is fine-tuned through transfer

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learning, augmented with a global average pooling layer, a 128-neuron dense layer, a dropout layer (0.3), and a softmax output head. This configuration produces the highest classification accuracy across all evaluated models.

3.6 Model Evaluation and Comparison

A systematic benchmarking research is conducted across all four architectures CNN, MobileNetV2, ResNet50, and EfficientNetB0 to identify the model best suited for accurate, low-latency tomato disease detection. Each model is assessed against the same held-out validation split under controlled, reproducible conditions.

3.6.1 Evaluation Metrics

To assess the performance of each model, standard classification metrics are used:

- **Accuracy**: Measures the overall correctness of the model
- **Precision**: Indicates how many predicted positive cases are correct
- **Recall**: Measures the ability of the model to identify actual positive cases
- **F1-Score**: Harmonic mean of precision and recall

The dataset is divided into **training and validation sets**, and models are evaluated on unseen data to ensure generalization.

3.7 Treatment Recommendation Module

Following disease classification, the predicted disease label is passed to a rule-based treatment recommendation module. This module queries a structured knowledge base that maps each of the 10 disease classes to a curated set of management options organised into three tiers: (i) chemical control (recommended fungicides or bactericides with dosage guidance), (ii) organic and biological remedies, and (iii) cultural and preventive measures such as crop rotation and pruning. The module returns the matching tier entries alongside the predicted class name and the model's confidence score, displaying all information on-screen in real time. This lookup-based design ensures deterministic, interpretable outputs at inference time without introducing additional model latency, following the approach described in [47].

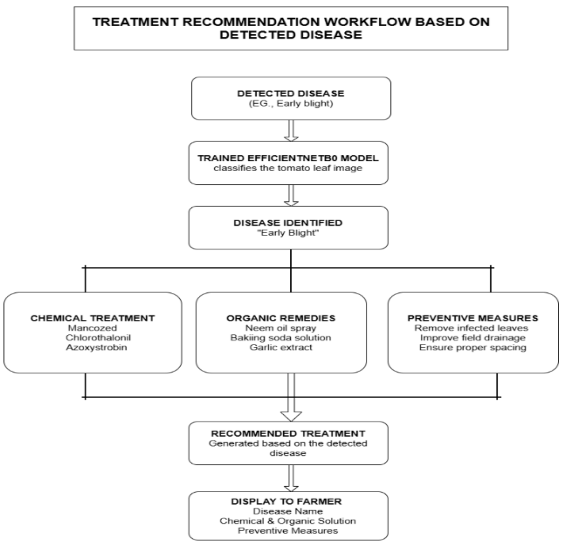

Figure-2:treatment recommendation workflow

3.8 Real-Time Detection

The final pipeline stage deploys the fine-tuned EfficientNetB0 model [45] for live inference via a standard webcam interface. Each captured frame is preprocessed in accordance with the standardized pipeline described in Section 3.3 and classified in real time. The on-screen output comprises the predicted disease label, the model's confidence score, and the corresponding treatment recommendations drawn from the rule-based knowledge base [47], constituting a complete, self-contained decision-support system for field-level farm management.

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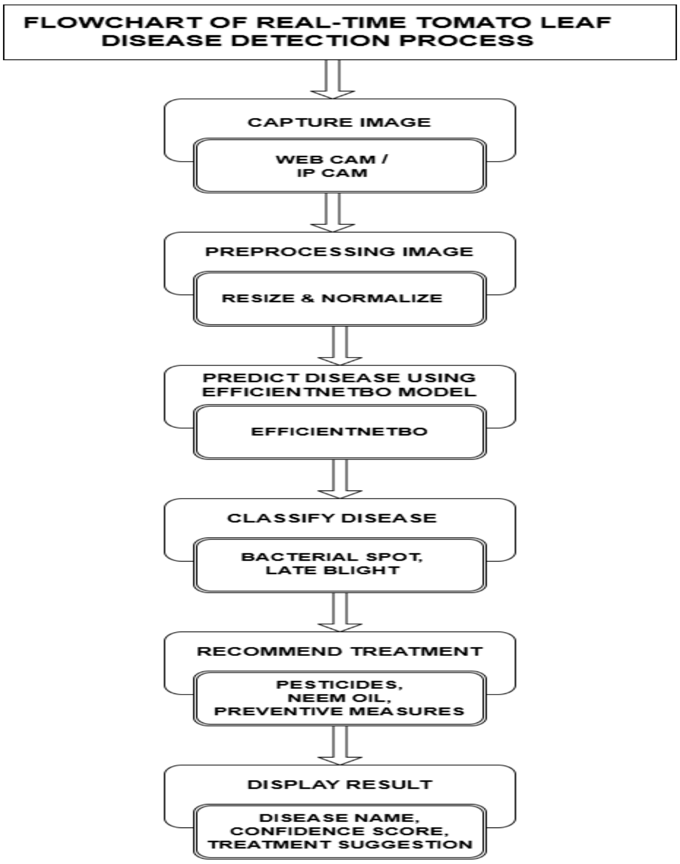

Figure-3: Real time detection process

IV. RESULT AND ANALYSIS

The performance of each model is measured using four widely adopted classification metrics: accuracy, precision, recall, and F1-score [14]. The PlantVillage dataset was partitioned into training and validation subsets in an 80:20 ratio; the training partition was used to optimize model weights, while the held-out validation partition was used solely to assess how well each model generalizes to previously unseen leaf images.

A comparative analysis was carried out using four deep learning models: CNN, MobileNetV2, ResNet50, and EfficientNetB0. All models were trained under identical conditions, including consistent preprocessing, data augmentation techniques, and training strategies, ensuring a fair and unbiased comparison.

Model	Accuracy (%)	Observations
CNN	91–93	Baseline performance with moderate feature extraction capability
MobileNetV2	97–98	Lightweight architecture suitable for real-time deployment
ResNet50	96–97	High classification accuracy due to deep residual learning
EfficientNetB0	≥98	Highest accuracy with optimized feature scaling

Table-1: Model accuracy and observation table

The results clearly indicate that transfer learning-based models outperform the baseline CNN, which learns all representations from scratch without prior knowledge [39][46]. Pre-trained networks capitalize on feature representations learned from large-scale image corpora, enabling faster convergence and higher classification accuracy on the tomato disease task.

Among the evaluated architectures, EfficientNetB0 [45] achieved the top classification score, benefiting from its compound scaling mechanism and effective fine-tuning. ResNet50 [44] delivered strong results attributable to its residual connections that support the training of deeper networks. MobileNetV2 [43], though marginally behind EfficientNetB0 in accuracy, presents a favorable efficiency-performance trade-off that makes it well suited for deployment on edge and resource-limited devices [15].

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Model	Accuracy (%)	Precision	Recall	F1-Score
CNN	92.1	0.92	0.92	0.92
MobileNetV2	97.5	0.97	0.97	0.97
ResNet50	96.4	0.96	0.96	0.96
EfficientNetB0	98.4	0.98	0.97	0.97

Table-2: Model comparison table

The confusion matrix analysis further confirms that the models are capable of accurately distinguishing between multiple tomato leaf disease classes, with minimal misclassification. Most errors occur between visually similar disease categories, which is expected in real-world agricultural datasets.

Beyond classification accuracy, the embedded treatment recommendation module substantially elevates the system's utility in agricultural practice. Each confirmed disease diagnosis triggers an immediate lookup in the knowledge base, surfacing targeted intervention options across chemical, organic, and preventive categories. This integration elevates the tool from a standalone classifier into a comprehensive farm advisory system.

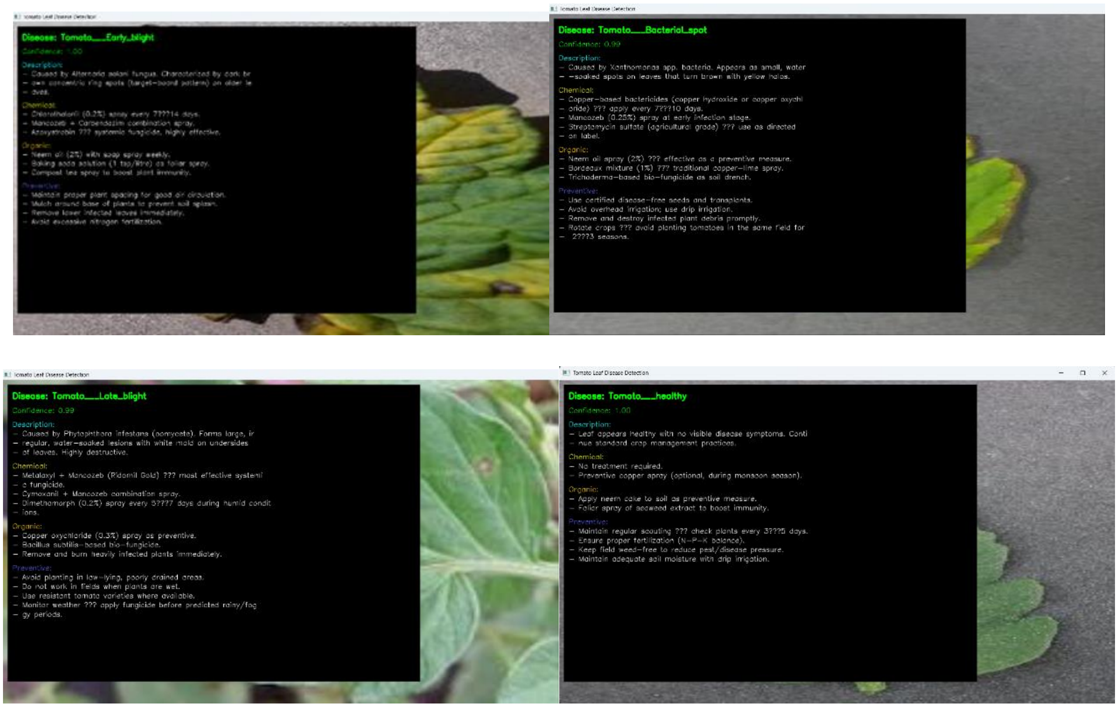

Image-2: real time detection output

V. CONCLUSION

This work presented a real-time tomato leaf disease classification and treatment recommendation system grounded in deep learning. A rigorous comparative evaluation was carried out across CNN, MobileNetV2 [43], ResNet50 [44], and EfficientNetB0 [45] under identical training conditions using the PlantVillage dataset [47]. The results confirm that transfer learning-based architectures substantially outperform the conventionally trained CNN baseline in classification performance [26][41].

EfficientNetB0 [45] attained the highest accuracy among the tested models owing to its principled compound scaling and fine-tuning strategy, while MobileNetV2 [43] offered a compelling balance between predictive performance and computational cost, making it viable for deployment on embedded or mobile platforms [15]. Coupling disease prediction with the rule-based treatment recommendation module [47] substantially broadens the practical scope of the system, translating automated classification into immediately actionable agronomic guidance.

In aggregate, the system delivers a scalable and practically deployable solution for precision agriculture, enabling proactive disease management, data-driven decision-making, and measurable improvements in crop productivity.

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VI. FUTURE WORK

Future efforts will focus on extending the dataset with real-field images captured under varying lighting and occlusion to improve generalization. Transformer-based architectures such as Vision Transformers will be explored as potential alternatives to EfficientNetB0. The static rule-based recommendation module will be upgraded to a dynamically updated agronomic knowledge base. Deploying the system on edge hardware such as Raspberry Pi or NVIDIA Jetson Nano would validate its feasibility for low-connectivity, resource-constrained farm environments where cloud-based inference is impractical. Additionally, expansion of the framework to other crops such as rice and wheat is planned to broaden the system's agricultural applicability.

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