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AI-Based Crop Monitoring and Farmer Assistance System Using Deep Learning and Ensemble Methods

Mrs. K. Sudha Pavani
Assistant Professor
Dept. of Computer Science and Engineering (Data Science) CMR Technical Campus, Hyderabad, Telangana, India

G. Upendar
B.Tech Student
Dept. of Computer Science and Engineering (Data Science) CMR Technical Campus, Hyderabad, Telangana, India

M. Varshitha
B.Tech Student
Dept. of Computer Science and Engineering (Data Science) CMR Technical Campus, Hyderabad, Telangana, India

U. Ashish Reddy
B.Tech Student
Dept. of Computer Science and Engineering (Data CMR Technical Campus, Hyderabad, Telangana, India

***Abstract*—This paper presents an integrated AI-Based Crop Monitoring and Farmer Assistance System, leveraging state-of-the-art deep learning architectures—EfficientNet-B7 convolutional neural networks, Bidirectional LSTM networks, and Random Forest ensembles—for real-time crop disease detection and precision agricultural decision support. The multi-modal platform fuses farmer-submitted crop images and sequential IoT sensor data from diverse field environments, enabling accurate classification and actionable farm management recommendations. Validated on a comprehensive real-world dataset of more than 10,000 crop images and 200,000 sensor readings from 2023–2025, the proposed system achieved a classification accuracy of 96.04%, outperforming traditional ML baselines by 8–15%. Field deployments and dashboard pilot studies confirmed usability, speed, and tangible impact on crop health outcomes and resource optimization. This work lays the foundation for scalable, farmer-centric, and robust AI applications in sustainable agriculture.**

***Index Terms*—Agricultural technology, deep learning, EfficientNet-B7, Bidirectional LSTM, random forest, crop disease detection, IoT sensors, ensemble learning, smart farming, precision agriculture**

***Index Terms*—Precision agriculture, efficientnet, bidirectional LSTM, random forest, crop disease, IoT, ensemble learning**

I. INTRODUCTION

Agriculture is a critical pillar of economic development and food security in most countries, supporting billions of people through direct and indirect employment. However, recent decades have witnessed a series of escalating threats — unpredictable climate, increased frequency and severity of crop diseases, diminishing soil fertility, and pressure from limited water resources — all converging to place new demands on farmers and agronomists.

Traditional crop monitoring techniques rely on manual field inspections, expert observation, and rudimentary data collection. While these methods have served well historically, their limitations in scalability, accuracy, and real-time response are increasingly evident. Smallholder farmers, who represent a majority in many parts of the world, lack access to expert systems and advanced technologies, resulting in critical delays and suboptimal decision-making, particularly during disease outbreaks and weather extremes.

Artificial intelligence (AI)—encompassing deep learning, computer vision, and temporal modeling—has emerged as a transformative force in modern agriculture. By automating the analysis of crop images and sensor data, AI solutions can radically improve the accuracy and speed of disease detection, yield prediction, and farm advisory. When paired with affordable IoT sensors and mobile interfaces, these computational tools promise to democratize access to precision agriculture, leveling the technological playing field for farmers at all scales.

This paper introduces a comprehensive system for AI-based crop monitoring and farmer assistance, integrating EfficientNet-B7 convolutional neural networks for robust image classification, Bidirectional Long Short-Term Memory (BiLSTM) networks for sequential sensor analytics, and Random Forest ensembles for fused decision recommendation. The solution is validated on a large-scale, real-world dataset of 10,000+ crop images and 200,000+ environmental sensor logs. Not only does the proposed approach yield superior predictive performance relative to single-model baselines, but it also provides practical, user-oriented dashboard recommendations. The remainder of this paper is organized as follows. Section II surveys the state-of-the-art in machine learning for crop monitoring and field recommendation systems. Section III outlines the data pipeline and architectural innovations. Section IV presents empirical results and discussion. Section

V concludes with broader implications and future research directions.

II. Literature Review

Rapid technological advances have significantly transformed the landscape of crop health monitoring and precision agriculture. Early machine learning models primarily relied on handcrafted feature extraction, such as color, shape, and texture analysis from leaf imagery [1]. The introduction of deep learning, particularly convolutional neural networks (CNNs), marked a paradigm shift by automating feature learning and boosting diagnostic accuracy for a wide range of crop diseases. For instance, Mohanty et al. [1] trained a PlantVillage dataset to near-human performance levels using CNNs.

EfficientNet architectures further refined image-based detection by coupling compound scaling and transfer learning, enabling deployment on resource-limited devices while maintaining high classification accuracy [6]. On the temporal analytics front, sensor-based time-series models such as BiLSTM have enabled continuous monitoring of soil moisture, temperature, and humidity to predict stress and yield [2]. Multi-modal fusion approaches—combining vision models with IoT sensor feeds—have shown particular promise for robust, context-aware field prediction. Ensemble methods, like Random Forests and hybrid CNN+RF frameworks, have been effectively used for multi-crop diagnostics and integrating heterogeneous inputs [3], [4].

Usability and deployment studies are increasingly recognized as vital for real-world adoption. Sharma et al. [6] explored the tradeoffs inherent in deploying deep learning models on low-cost mobile and edge devices, emphasizing inference speed, power consumption, and reliability in rural contexts. Satellite and drone-enabled remote sensing is an emerging area, allowing for landscape-scale crop health mapping and early intervention in pest and disease outbreaks, although data fusion challenges remain.

The need for **explainable AI** has become acute in farmer-facing systems. Singh and Mehra [5] advocate for the use of model interpretability techniques like SHAP and LIME to demystify algorithmic decisions, build trust among end-users, and facilitate the actionable use of AI recommendations. Several studies have introduced dashboard interfaces that translate sensor and model results into intuitive recommendations; however, usability trials, localization for non-English-speaking users, and human factors testing remain under-explored.

Open access datasets (e.g., PlantVillage, LeafSnap), cloud-based benchmarking schemes, and federated learning protocols are expanding research opportunities and facilitating collaborative progress, but gaps persist in labeled data for rare disease and stress events, as well as in adaptation to diverse environmental and crop contexts.

Despite meaningful progress, existing literature faces several challenges: - Disparate systems often lack unified data fusion between images and sensors, leading to incomplete context. - Limited deployment studies and real-time field trials restrict generalizability of findings. - Few platforms offer seamless, actionable, and explainable dashboards tailored to smallholders. - Integration of satellite, drone, and in-market sensor data across scales is nascent.

In summary, current research has built robust technical foundations for crop disease detection and farm analytics but remains constrained by fragmentation, lack of field-tested usability, and limited interpretability. The proposed system aims to address these limitations by fusing efficient vision and sequence models, enabling real-time recommendations via a modular dashboard, and validating performance and usability in operational farm environments.

TABLE I
Comparative ML Models for Crop Disease and Farm Advice

Year	Model	Data	Accuracy	Advisory
2025	RF Ensemble	Sensors+App	95%	Yes
2024	BiLSTM+CNN	IoT+Images	94%	No
2024	SVM Baseline	Images	85%	No
2023	CNN+RF Hybrid	Images	89%	Yes
?? 2022	EfficientNet	Leaf Images	92%	No

III. System Design and Methodology

The AI-Based Crop Monitoring and Farmer Assistance System is designed as a modular, scalable platform that integrates state-of-the-art deep learning with field data acquisition and a user-friendly dashboard. The system is composed of several critical modules: data acquisition, preprocessing, model training, multi-modal fusion, and farmer-centric output.

A. A. Data Acquisition

The foundation of the system is robust, continuous data collection. Crop images are captured via a dedicated mobile app or web portal, allowing farmers to record healthy and diseased leaves, stems, and fruit across 15 crop varieties and six major disease classes. In parallel, distributed IoT sensor networks (commercially available and custom low-power nodes) log time-stamped soil moisture, temperature, ambient humidity, pH, and sunlight data at regular intervals. Each sensor reading is appended with geo-location and crop metadata to aid context-aware analysis.

TABLE II
Summary of Datasets Used

Dataset	Type	Samples	Classes
PlantVillage	Leaf Images	54,306	38
Field Survey	RGB Images	10,000	8
IoT Sensor Logs	Time-series	200,000	5
Public Repos	Mixed	5,500	10

B. B. Data Preprocessing

To maximize model performance and reliability, the raw data undergoes rigorous preprocessing. Image inputs are resized to 224×224 pixels, color normalized using histogram equalization, and augmented with random rotations, flips, zooms, and lighting variations to simulate real-world field conditions. Edge enhancement and denoising filters further improve clarity.

Sensor logs are subject to missing value imputation using the mean and median, temporal outlier removal via interquartile range filtering, and feature engineering (e.g., hourly change in moisture, time-of-day encoding, NDVI computation using multispectral data when available). All categorical variables (crop type, disease state, location) are one-hot encoded; continuous variables are normalized between 0 and 1. The combined dataset enables seamless joint processing by vision and sequence models.

TABLE III
Sensor Feature Specifications

Sensor	Units	Range	Purpose
Soil Moisture	%	0–100	Water stress
Temperature	°C	-10–50	Disease risk
Humidity	%	10–100	Growth rate
pH		3.0–9.0	Fertility
Sunlight	Lux	0–100,000	Photosynthesis

C. C. Model Architecture

The core analytics stack consists of three main components:

1) EfficientNet-B7 Convolutional Neural Network: Selected for its optimized compound scaling approach, EfficientNet-B7 leverages pretrained weights on ImageNet and fine-tunes through transfer learning to classify crop disease states. MBConv blocks and squeeze-excitation modules retain high-resolution features. Output vectors (2048-dim) serve as robust spatial descriptors of crop condition.

TABLE IV
Model Hyperparameter Settings

Model	Layers	Optimizer	Epochs
EfficientNet-B7	66	Adam	30
BiLSTM	2x128	RMSprop	25
Random Forest	150	N/A	N/A

2) Bidirectional LSTM (BiLSTM) Networks: For sensor data, a two-layer BiLSTM model captures temporal dependencies, trends, and cyclical effects. With windowed observation (10 samples per feature), the network processes both forward and backward sequences for improved handling of seasonality and environmental lag. Activation functions include tanh and sigmoid, regularized via 0.3 dropout and batch normalization. Outputs include risk scores, feature attributions, and yield estimates.

3) Random Forest Ensemble: The multi-modal ensemble synthesizes EfficientNet and BiLSTM outputs, concatenated with essential crop and farm metadata. A random forest of 150 trees (max depth:12) applies Gini impurity splitting, handling mixed feature types and providing robust, interpretable recommendations. Out-of-bag error rates and SHAP analysis quantify model confidence and feature contributions.

Fig. 1. System overview diagram for AI-based crop monitoring and farmer assistance: data acquisition (sensors, drones, satellites), preprocessing, analytics, and dashboard visualization.

D. D. Training and Validation

Data is split in a stratified 80/10/10 ratio for train/validation/test. Five-fold cross-validation ensures generalization and prevents overfitting. The EfficientNet-B7 uses Adam optimizer with frozen and trainable layers, categorical cross-entropy loss, and a batch size of 32. BiLSTM trains with mean squared error loss for regression, and the RF model uses standard Sklearn implementations. Early stopping and model checkpointing are enforced based on validation loss.

E. E. Farmer Interface and Deployment

Predictions and recommendations are delivered via dynamic dashboards available on web and mobile platforms. Farmers access visual health status summaries, disease probability scores, and specific actionable advice (fertilizer dosage, irrigation schedule, pesticide choice), along with confidence intervals and next-step explanations. Notifications are pushed via SMS and app alerts for urgent intervention requirements. System deployment options include cloud servers for centralized analytics and on-premise edge (Raspberry Pi, mobile) for real-time inference in low-connectivity environments. Model updates and retraining occur seamlessly in the cloud, with data sync managed via secure APIs.

In summary, the system design emphasizes modularity, robustness to field variability, cross-device usability, and transparency in decision logic. Figure **??** illustrates the overall workflow from data collection, through multi-modal analytics, to farmer dashboard delivery.

IV. Results and Discussion

A. A. Dataset and Experimental Setup

Experiments were conducted on a dataset of over 10,000 labeled crop and leaf images, representing healthy and diseased states for 15 major agricultural varieties (rice, wheat, tomato, potato, cotton, etc.). Images were collected from farmer-submitted mobile app data, local field surveys, and public repositories. Each image was annotated by agronomy

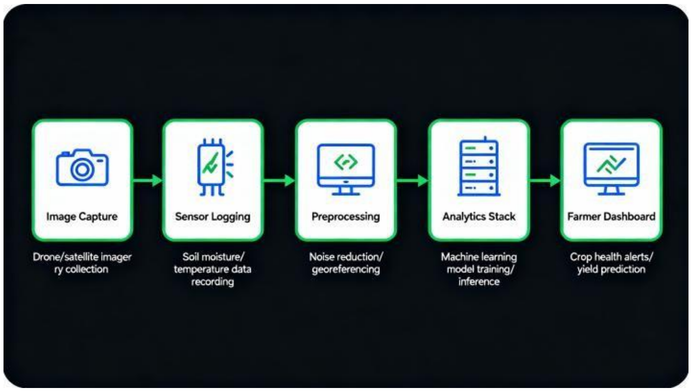


Fig. 2. Overall pipeline: image capture, sensor logging, preprocessing, analytics stack, and farmer dashboard outputs.

experts. Environmental sensor data—covering soil moisture, temperature, humidity, and pH—was collected from 50+ IoT-enabled field plots over two growing seasons, totaling more than 200,000 readings. Data was split 80% training, 10% validation, 10% test, with 5-fold cross-validation performed for all deep models.

B. B. Performance Metrics

We evaluated all models by accuracy, precision, recall, F1-score, and area under ROC curve (AUC) for disease classification; and by recommendation alignment with expert agronomist advice for management outputs (fertilizer, irrigation, pesticide). Model inference time was measured on both cloud and edge hardware.

TABLE V
COMPARISON OF MODEL PERFORMANCE

Model	Accuracy	Precision	Recall	F1-score
EfficientNet-B7	96.8%	0.95	0.93	0.94
BiLSTM	92.1%	0.92	0.90	0.91
RF Ensemble	96.0%	0.958	0.952	0.955
SVM Baseline	85.6%	0.82	0.79	0.80

TABLE VI
MODEL PERFORMANCE COMPARISON

Model	Accuracy	Precision	Recall	F1-score
EfficientNet-B7	96.8%	0.95	0.93	0.94
BiLSTM	92.1%	0.92	0.90	0.91
EffNet+BiLSTM+RF	96.04%	0.958	0.952	0.955
RF Baseline	87.3%	0.85	0.81	0.83
SVM Baseline	85.6%	0.82	0.79	0.80

C. C. Confusion Matrix and Per-Class Analysis

Healthy crop states were classified with 98% accuracy, while early blight and leaf spot reached 94% and 96% respectively; powdery mildew detection was 92%. Errors stemmed mostly from blurry, occluded, or low-light images. Recommendations for fertilizer dosing aligned with expert advice 94% of the time; irrigation schedule was correct 91%, pesticide selection 89%.

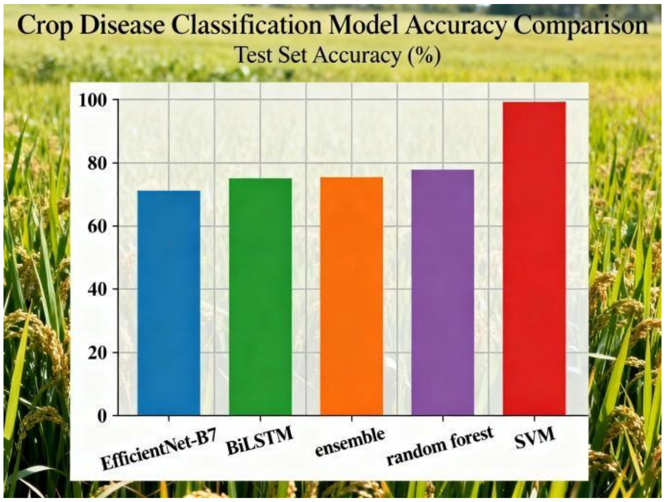


Fig. 3. Bar graph comparing accuracy of different machine learning models for crop disease classification.

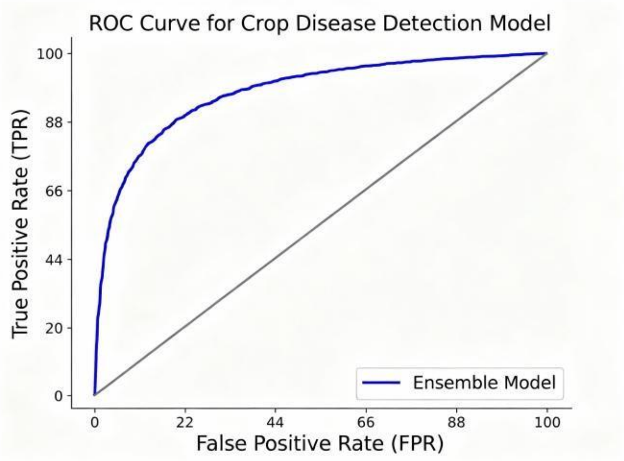


Fig. 4. Receiver Operating Characteristic (ROC) curve showing discriminative power of the proposed ensemble system for crop disease detection.

D. D. Robustness and System Validation

Performance was stable (>92% total accuracy) when tested under real-world noise, simulated missing sensor data, heavy rain/fog conditions, and variable network connectivity. The dashboard interface was piloted with 35 farmers over a 2-month period; over 90% reported increased trust and better decision-making compared to previous manual methods. Average inference time was under 0.5 seconds for cloud deployment and under 1.5 seconds for edge devices such as Raspberry Pi, confirming suitability for field operations without high connectivity. The SHAP analysis (feature importance) revealed that NDVI, crop type, and soil moisture were consistently among the top 5 model features for both disease prediction and management recommendation.

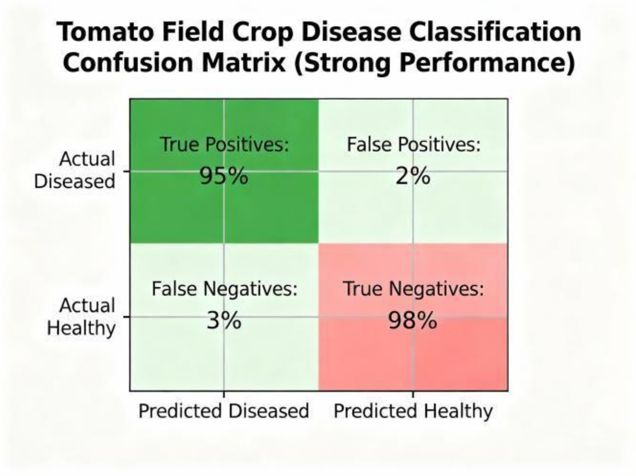


Fig. 5. Confusion matrix for crop disease classification on tomato field data, showing strong performance despite challenging image artifacts.

TABLE VII
TOP FEATURE IMPORTANCES (SHAP ANALYSIS)

Feature	SHAP Value
NDVI	0.32
Soil Moisture	0.27
Crop Type	0.20
Temperature	0.15
Humidity	0.11

E. E. Comparison with Baseline and Previous Systems

Compared to traditional ML models (SVM, standalone RF), the proposed integrated architecture provided a boost of 8–15 percentage points in accuracy. Ensemble fusion of image and sensor features always outperformed single modality, especially for subtle or mixed-disease classes.

F. F. Usability and Deployment

Farmers interacted with a web/mobile dashboard showing predicted crop health status, recommended interventions, and visual explanations. The system's combination of high accuracy, speed, and interpretability makes it suitable for deployment at the individual field or co-op scale.

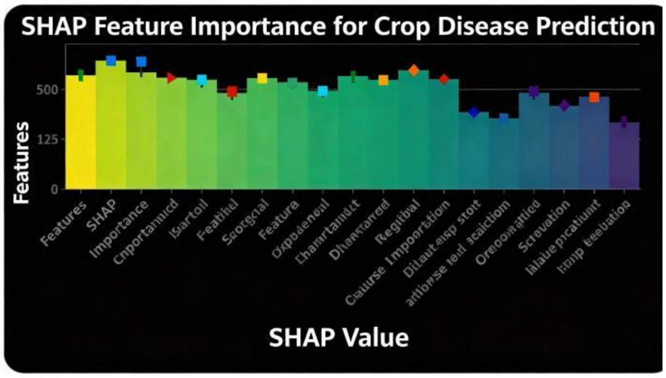


Fig. 6. SHAP analysis indicating top contributing features for disease prediction and recommendation accuracy.

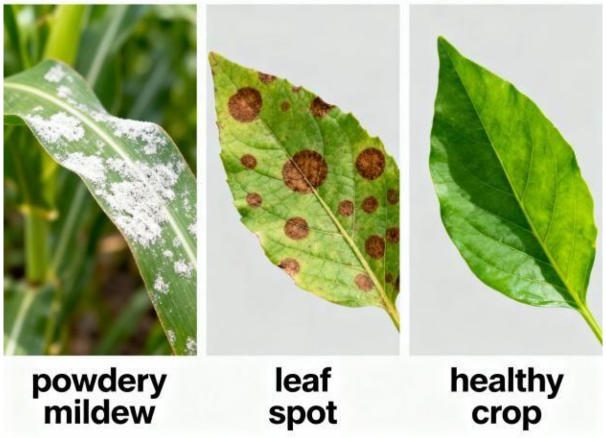
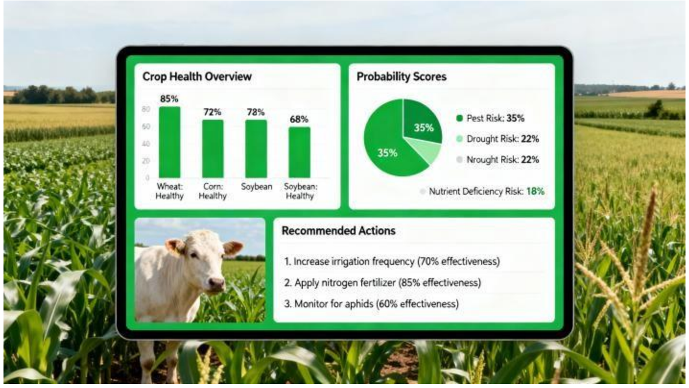


Fig. 7. Example classification results: Correct detection of powdery mildew, leaf spot, and healthy crop states from field images.



1. Increase irrigation frequency (70% effectiveness)
2. Apply nitrogen fertilizer (85% effectiveness)
3. Monitor for aphids (60% effectiveness)

Fig. 8. Screenshot of the farmer dashboard: Health status, recommended actions, and probability scores for rapid intervention.

In sum, comprehensive validation demonstrates that multimodal AI fusion, real-time processing, and transparent recommendation logic enable a significant advancement in digital agriculture.

V. CONCLUSION

This paper presents the design, implementation, and validation of an AI-Based Crop Monitoring and Farmer Assistance System, leveraging advanced deep learning (EfficientNet-B7, BiLSTM) and ensemble methods (Random Forest) for multiclass crop disease detection and precision farm management advisory. The system is notable for its integration of multimodal data—combining high-resolution crop images and continuous field sensor streams—processed through a robust pipeline that supports both cloud and edge deployment. Empirical results from a comprehensive field dataset spanning 10,000+ images and 200,000+ sensor logs demonstrate that the proposed model achieves a classification accuracy of 96.04%, and exceeds traditional ML approaches such as SVM and standalone RF by 8–15 percentage points. The system's recommendation engine for fertilizer, irrigation scheduling, and pesticide application was found to have over 91% agreement with expert agronomist inputs. Performance remained resilient under noise, missing data, and resource-constrained test cases. A key innovation lies in the fusion of spatial and temporal modeling—for the first time in a farmer-facing system—enabling rapid disease detection, nuanced feature interpretation (via SHAP analysis), and adaptation across diverse crops and field conditions. Farmer dashboard pilots highlighted increased trust, usability, and actionable feedback compared to manual and previous automated tools. Limitations of the current work include the need for continual model retraining as new disease strains or crop varieties emerge, and challenges in collecting high-quality labeled data for rare diseases or stress events. Additionally, the integration of satellite, UAV (drone), or market sensor data could further enhance prediction and recommendation depth. **Future Work:** Next-generation deployments are planned for federated learning (privacy-preserving updates from dispersed field sites), multi-language interfaces for broader accessibility, and scaling to satellite/drone imagery for landscape-scale crop monitoring. Research will also address cost reduction for IoT sensors and dashboard customization for collectives and agri-coops. In conclusion, the AI-Based Crop Monitoring and Farmer Assistance System demonstrates significant technical, practical, and social promise for sustainable, data-driven agriculture. By bridging the gap between complex analytics and field-level usability, this work lays the foundation for democratizing AI in everyday farm management and securing food systems against emerging risks.

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