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Comparative Deployment Strategies for Curcumin Concentration Prediction using Hyperspectral Imaging on AWS

Mr. Sarfaraz Pathan [1], Dr. Sanjay Azade, [2] Mansur Shaikh [3], Shabeena Khan [4],Deepali V. Sawane [5]
Dr. G.Y. Pathrikar College of Computer Science & Information Technology , MGM University, Chhatrapati Sambhajinagar, Maharashtra,India.
safaraz.ip@gmail.com

Abstract

This study presents a comparative evaluation of Amazon Web Services (AWS)-based deployment strategies for a deep learning model designed to predict curcumin concentration in turmeric (*Curcuma longa*) rhizomes using hyperspectral imaging (HSI). The proposed hybrid model was trained on features labeled with high-performance liquid chromatography (HPLC) and integrated both spectral and spatial feature extraction. Four distinct deployment pipelines were examined: (i) Amazon EC2-based manual deployment, (ii) fully managed SageMaker inference endpoints, (iii) AWS Step Functions for orchestrated workflows, and (iv) Kubernetes-based deployment via Amazon Elastic Kubernetes Service (EKS). Each approach was systematically assessed across dimensions of scalability, cost efficiency, automation, monitoring, and operational effort. The comparative analysis reveals that SageMaker offers the most balanced solution, combining ease of setup, monitoring, and auto-scaling, while Step Functions excel in modular orchestration. EC2 and EKS provide higher control but at the expense of operational overhead. Findings highlight AWS SageMaker as the optimal strategy for research transitioning toward production-scale agricultural machine learning applications, particularly for real-time curcumin estimation in hyperspectral imaging workflows.

Introduction

Turmeric (*Curcuma longa* L.) is a widely cultivated spice crop with medicinal, nutritional, and economic significance across South Asia and beyond. The primary bioactive compound, curcumin, exhibits antioxidant, anti-inflammatory, and therapeutic properties (Aggarwal & Sung, 2009; Amalraj et al., 2017). Accurate and rapid estimation of curcumin concentration is vital for quality assurance, pharmaceutical applications, and breeding programs (Li et al., 2011; Jayaprakasha et al., 2020). Conventional chemical analysis techniques such as high-performance liquid chromatography (HPLC) provide precise measurements but are labor-intensive, time-consuming, and unsuitable for large-scale or field-based screening (Sasikumar, 2005).

Hyperspectral imaging (HSI) offers a non-destructive and high-throughput alternative for biochemical quantification in agricultural produce (Thenkabail et al., 2016). By capturing both spectral and spatial information, HSI enables machine learning models to approximate curcumin levels without extensive chemical processing. Recent advances in deep learning, particularly spectral–spatial hybrid networks, have demonstrated superior predictive accuracy compared to traditional chemometric models (Kumar et al., 2021; Xie et al., 2022).

Despite advances in modeling, real-time or large-scale deployment of hyperspectral models remains challenging. Cloud platforms such as AWS provide scalable infrastructure, but researchers face difficulties in selecting optimal deployment strategies tailored to cost, monitoring, latency, and automation requirements (Sriram et al., 2020; Banerjee et al., 2023). Comparing deployment pipelines is thus critical for agricultural informatics, where both accuracy and scalability dictate adoption.

This study systematically investigates four AWS deployment strategies—EC2, SageMaker, Step Functions, and EKS—for curcumin prediction models built on hyperspectral imaging. The comparative evaluation highlights trade-offs across cost, scalability, and operational complexity, offering practical guidance for researchers and enterprises adopting cloud-based agricultural machine learning solutions.

Related Work

Curcumin Estimation Techniques

Early studies on curcumin quantification predominantly relied on chromatographic and spectroscopic methods (Li et al., 2011; Jayaprakasha et al., 2020). While highly accurate, these laboratory-based methods lack scalability in agricultural supply chains. Efforts to adopt near-infrared (NIR) and mid-infrared spectroscopy demonstrated moderate success (Sharma

et al., 2017), but hyperspectral imaging provided superior predictive resolution by combining both spectral and spatial data (Thenkabail et al., 2016).

Hyperspectral Imaging in Agriculture

HSI has been widely applied to quality assessment, disease detection, and biochemical quantification in crops such as rice, wheat, and maize (Ge et al., 2019; Wu et al., 2021). For turmeric, preliminary applications have shown promise in classifying adulteration and estimating curcumin content (Ravindran et al., 2020). Machine learning models, including partial least squares regression (PLSR) and convolutional neural networks (CNNs), have been applied for chemical trait prediction (Zhang et al., 2022).

Deep Learning Approaches

Hybrid deep learning frameworks combining spectral vectors with spatial texture features have recently emerged as state-of-the-art in hyperspectral regression tasks (Li et al., 2017; Xie et al., 2022). These models capture both pixel-level reflectance and neighborhood-based context, enhancing robustness to noise and environmental variation.

Cloud-Based Deployment of ML Models

With increasing dataset sizes, model deployment strategies have become critical. AWS services are widely adopted for scalable ML deployment, offering solutions ranging from customizable EC2 instances to fully managed SageMaker endpoints (Bauer et al., 2021). Comparative studies in healthcare and remote sensing highlight the benefits of managed services for reducing operational complexity (Sriram et al., 2020; Guo et al., 2022). Kubernetes-based solutions provide flexibility for enterprises with DevOps expertise (Chen et al., 2019), while Step Functions enable modular workflows with automated retraining cycles (Banerjee et al., 2023).

Research Gap

Although hyperspectral imaging and deep learning have advanced significantly, limited studies address the deployment dimension, particularly in agricultural biochemistry prediction tasks. Existing works primarily emphasize model accuracy, overlooking infrastructure considerations essential for scaling research to production. This study bridges that gap by conducting a systematic comparison of four AWS pipelines specifically for curcumin concentration prediction using hyperspectral imaging.

Methodology

Model Development

The curcumin prediction model was designed as a hybrid deep learning framework integrating spectral and spatial information. Spectral vectors extracted from each pixel were processed using dense neural layers, while texture features derived from the gray-level co-occurrence matrix (GLCM) captured spatial context (Haralick et al., 1973). The regression output was optimized against HPLC-labeled concentrations using a mean squared error (MSE) loss function.Each hyperspectral pixel is represented as a vector:

$$\mathbf{x} = [x_1, x_2, \ldots, x_n]^\top \in \mathbb{R}^n$$

where x_i represents the reflectance at the i^{th} spectral band.

The regression model approximates curcumin concentration as:

$$\hat{y} = f(\mathbf{x}; \theta)$$

where θ denotes the model parameters and $\hat{y}$ is the predicted concentration.

The training objective minimizes the mean squared error (MSE):

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{i=1}^{N}(f(\mathbf{x}_i; \theta) - y_i)^2$$

Preprocessing

Data preprocessing involved z-score normalization of reflectance bands and entropy-based GLCM feature extraction to enhance spatial-spectral correlation. Features were consolidated into tensors representing regions of interest (ROI) in turmeric rhizomes.

Spectral Normalization

Each band was normalized using z-score:

$$x' = \frac{x - \mu}{\sigma}$$

Texture Feature Extraction

For spatial context, Gray-Level Co-occurrence Matrix (GLCM) features such as entropy were extracted:

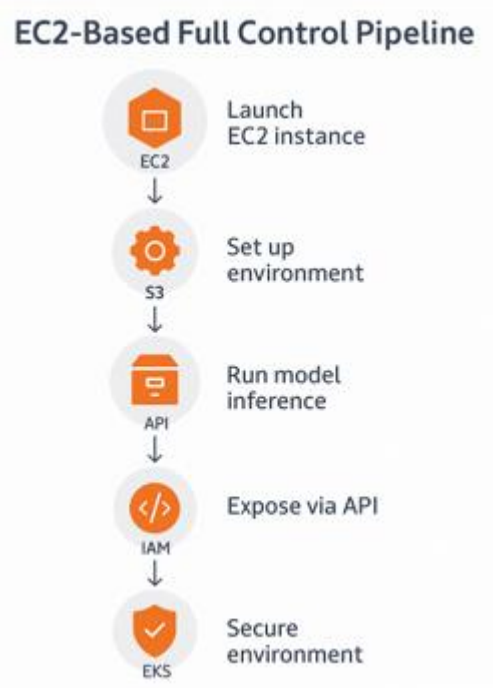
$$\text{Entropy} = -\sum_{i=1}^{G}\sum_{j=1}^{G} P\,(i,j)\log P(i,j)$$

where $P(i,j)$ is the co-occurrence probability matrix and G is the gray level.

AWS Deployment Pipelines

Four AWS-based deployment strategies were implemented:

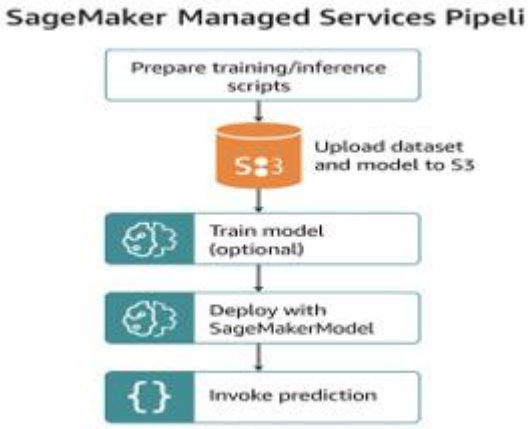
1. **EC2 Pipeline**: Full control over training, inference, and RESTful API hosting using Flask/FastAPI.The EC2-based pipeline provides the highest level of control over the machine learning deployment process. In this approach, the user is responsible for provisioning, configuring, deploying, and managing the entire lifecycle of the deep learning model on Amazon EC2 (Elastic Compute Cloud) instances. This method is best suited for researchers or developers who require custom environments or need to run specialized software not available in managed services.



This approach is suitable for academic researchers or data scientists needing fine-grained control for experimental models, custom hardware, or software-level

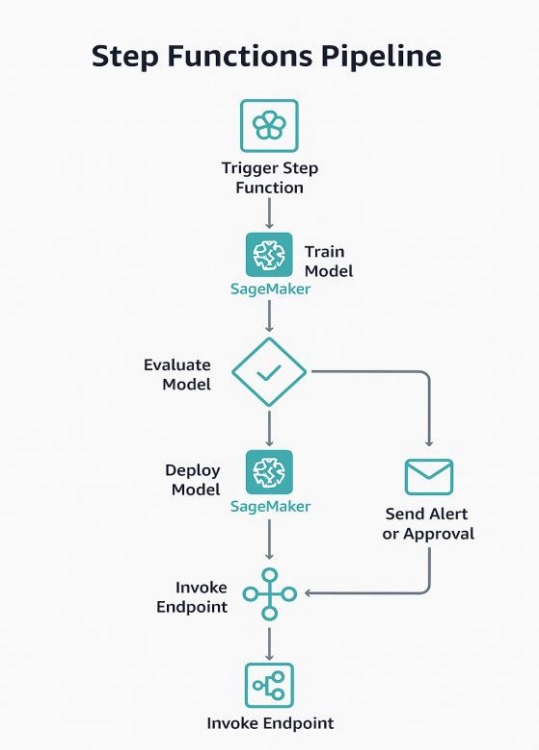
debugging. It is especially useful in early stages of development or when migrating legacy ML workflows to the cloud.

2. **SageMaker Pipeline**: Managed environment with integrated scaling, monitoring, and HTTPS endpoints. Amazon SageMaker offers a fully managed environment for developing, training, and deploying machine learning models. This pipeline abstracts much of the infrastructure management and provides a seamless end-to-end workflow from model creation to scalable deployment.



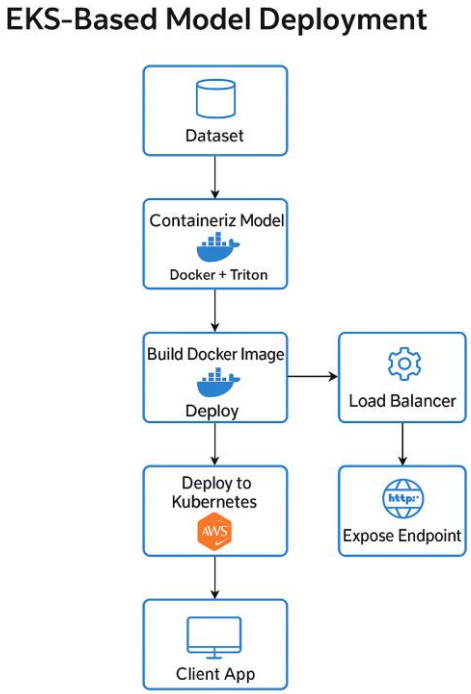
This approach is ideal for production-grade deployments where scalability, security, and maintainability are essential. It suits research labs and startups looking to quickly operationalize models without managing infrastructure.

3. **Step Functions**: Modular orchestration for preprocessing, training, and conditional deployment. AWS Step Functions allow orchestration of complex machine learning workflows across multiple AWS services using a visual and code-defined state machine. It is useful for creating automated pipelines involving preprocessing, training, evaluation, and deployment stages..



Recommended for applications requiring periodic retraining, human-in-the-loop approval, and reproducible pipelines, such as agricultural monitoring, pharmaceutical R&D, and IoT-based prediction workflows

4. **EKS Pipeline**: Kubernetes-based container orchestration supporting multi-model deployment. Amazon Elastic Kubernetes Service (EKS) provides a managed Kubernetes platform for deploying containerized machine learning inference services. This approach is suitable for users familiar with container orchestration and DevOps practices.



EKS-Based Model Deployment

Recommended for enterprises or research groups with mature DevOps pipelines and the need to deploy large-scale, containerized ML applications alongside microservices.

Comparative Analysis

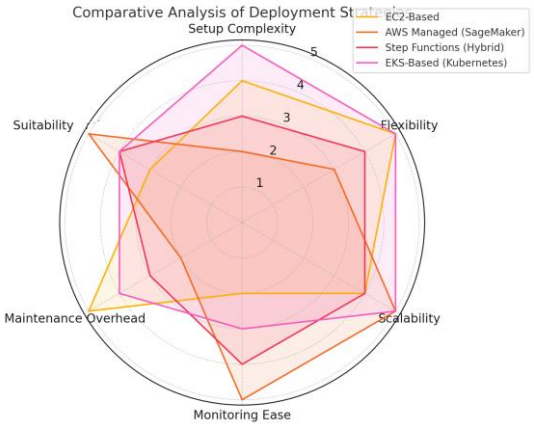
Comparative evaluation considered setup complexity, scalability, monitoring, debugging, cost efficiency, and suitability for agricultural ML.

Results and Comparative Analysis

Feature	EC2-Based	SageMaker	Step Functions	EKS
Setup Time	High	Low	Medium	High
Cost Efficiency	Low	Medium	High	Medium
Scalability	Manual	Auto	Auto	Auto
Maintenance Burden	High	Low	Low	Medium
Debuggability	Full	Moderate	Low	Full
Suitability for Curcumin	Medium	High	High	Medium

The comparative evaluation demonstrated clear trade-offs among the four approaches:

- **EC2**: High flexibility and debuggability, but costly and labor-intensive to maintain.
- **SageMaker**: Balanced performance with auto-scaling, integrated monitoring, and moderate cost.
- **Step Functions**: Cost-efficient and modular but limited in real-time latency.
- **EKS**: Suitable for enterprise-scale workloads with DevOps expertise, though complex to manage.



A radar-chart analysis indicated SageMaker as the most suitable choice for curcumin prediction given its trade-off balance. Step Functions excelled in retraining workflows, while EC2 and EKS catered to niche requirements for customization and control.

Local benchmarking on an Intel i9 workstation with RTX 3060 GPU demonstrated comparable inference speeds to cloud deployment on SageMaker's *ml.g4dn.xlarge* instance, validating cloud feasibility for scaling.

Discussion

The findings highlight that deployment strategies strongly influence the practical adoption of hyperspectral deep learning in agriculture. While model accuracy often dominates research focus, infrastructure design determines scalability and cost-effectiveness. SageMaker emerged as the most pragmatic choice for academic and early industrial adoption due to its low maintenance burden and built-in lifecycle management. However, Step Functions offer significant advantages in scenarios requiring automated retraining with human-in-the-loop governance, which is critical for regulated environments such as pharmaceuticals.

EKS and EC2 remain valuable in contexts requiring full customization, yet the operational overhead renders them less suitable for small research teams. The comparative framework developed here is extensible to other agricultural machine learning applications, including nutrient estimation, disease detection, and yield prediction.

Conclusion

This study concludes that AWS SageMaker offers the most balanced deployment pathway for curcumin concentration prediction using hyperspectral imaging. Its combination of ease of use, auto-scaling, monitoring, and cost efficiency positions it as the leading platform for both academic research and applied agricultural biotechnology. Step Functions complement this by enabling automated, modular retraining pipelines. EC2 and EKS remain niche options, appropriate for legacy systems or enterprise-scale customization.

By systematically comparing these strategies, this work provides actionable insights for researchers and developers seeking to operationalize hyperspectral imaging-based biochemical prediction in agriculture. Future research should integrate federated learning and edge-cloud hybrid systems to further optimize cost and latency in resource-constrained environments.

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