Worldwide Journal of Creative Research and Thoughts (WJCRT)
ISSN (Online): 3143-7850
Volume-2 Issue-3 || Jul – Sep 2026 || PP. 52-60
https://wjcrt.org/

AI-Enabled Agricultural Evaluation of Seaweed Biostimulants for Tomato Growth, Yield, and Quality

Dr Bibhu Santosh Behera

Post Doctoral Researcher

Lincoln University and Mission Manager

Farm Livelihoods, Ministry of Rural Development, Govt of Indi

Orcid id- https://orcid.org/0009-0000-6232-1510

http://www.wjcrt.org/ || Vol. 2 No. 3 (2026): September Issue

Date of Submission: 06-08-2026	**Date of Acceptance:** 20-08-2026	**Date of Publication:** 06-09-2026

Abstract— Seaweed-derived biostimulants are increasingly investigated as sustainable crop inputs capable of improving plant development, productivity, fruit quality, and tolerance to environmental stress. However, conventional evaluations generally depend on periodic destructive measurements and end-of-season observations, providing limited information on the temporal and nonlinear responses of tomato plants to different biostimulant concentrations. This study proposes an AI-enabled agricultural evaluation framework that combines longitudinal RGB–multispectral plant imaging, physiological measurements, environmental observations, and conventional agronomic traits for evaluating seaweed biostimulant responses in tomato (*Solanum lycopersicum* L.). The central research gap concerns the absence of integrated predictive systems capable of linking early phenotypic responses to subsequent yield and fruit-quality outcomes while simultaneously identifying an agronomically optimal biostimulant dose. A multimodal learning strategy is conceptualized to extract canopy-growth signatures, vegetation characteristics, flowering dynamics, fruit-development traits, and environmental interactions across untreated and seaweed-treated plants.
Keywords— Seaweed biostimulants, Tomato, Artificial intelligence, Multimodal phenotyping, Precision agriculture, Yield prediction

Introduction

Plant biostimulants occupy an increasingly important position within this transition because their principal function is associated with stimulation of plant nutrition processes, nutrient-use efficiency, crop quality, and tolerance to abiotic stress rather than conventional direct fertilization. Seaweed-derived formulations constitute one of the most widely studied categories of biostimulants because marine algae contain diverse biologically active compounds, including polysaccharides, phenolic substances, pigments, amino-acid-related compounds, minerals, and hormone-like signaling molecules.

Tomato (*Solanum lycopersicum* L.) represents an appropriate model horticultural crop for investigating these inputs because its commercial performance depends not merely on vegetative biomass but on the coordinated development of flowering, fruit set, fruit size, marketable yield, visual characteristics, soluble solids, firmness, antioxidant constituents, and postharvest attributes. Consequently, an intervention that stimulates shoot development without producing corresponding improvements in reproductive performance may have limited commercial value. Likewise, maximizing fruit weight while compromising soluble solids or firmness may be undesirable for specific fresh-market or processing applications.

Recent experimental evidence suggests that seaweed-derived formulations can influence multiple dimensions of tomato performance. A greenhouse investigation using polysaccharide-enriched extracts from several Moroccan seaweeds found improvements in tomato growth, yield, and fruit-quality characteristics, with the chemical composition of the extracts showing associations with the observed plant responses. Research involving *Ascophyllum nodosum*-containing products has similarly demonstrated measurable changes in morphological, physiological, yield, and quality characteristics under tomato cultivation. More recent physiological and molecular research indicates that *A. nodosum*-derived treatment can influence drought tolerance, photosynthetic maintenance, senescence-associated processes, metabolites, and stress-related molecular pathways, suggesting that the response to seaweed formulations involves considerably more than a simple fertilizer effect.

Nevertheless, the evidence base also demonstrates substantial heterogeneity. Treatment effectiveness varies with seaweed species, extraction technology, formulation composition, application route, concentration, growth stage, environmental conditions, cultivar, and production system. A 2024 review of horticultural applications highlighted broad potential for seaweed extracts in enhancing crop performance and stress tolerance while also emphasizing differences among formulations and application strategies. A tomato-specific meta-analysis published in 2026 further documented concentration-dependent variation across growth, yield, physiological, and quality outcomes, illustrating why assuming a universally beneficial response to increasing seaweed concentration is scientifically inappropriate.

This variation creates an important practical problem. Conventional agronomic experiments frequently evaluate treatment effects using discrete observations such as plant height at selected intervals, destructive biomass estimation, final fruit number, total yield, or laboratory-based quality measurements. Such measurements remain indispensable for experimental validation, but they provide only intermittent snapshots of a biological process that develops continuously. Two plants may ultimately reach similar height yet follow substantially different growth trajectories, canopy expansion rates, flowering patterns, stress responses, or fruit-development pathways. These temporal differences can contain information that is lost when treatment performance is evaluated predominantly through final averages.

Artificial intelligence and high-throughput plant phenotyping create an opportunity to overcome this limitation. Computer vision can convert repeated images into quantitative measurements of canopy structure, leaf distribution, color dynamics, fruit development, and other phenotypic characteristics. Recent work on tomato phenotyping has demonstrated that advanced image-based reconstruction can estimate morphological characteristics including internode length, leaf area, and fruit volume with strong agreement to manually derived measurements. Multimodal deep-learning approaches have also demonstrated that combinations of RGB, near-infrared, and depth information can outperform individual imaging modalities for detecting tomato water status, indicating the value of complementary sensing channels for representing plant physiological conditions. Similarly, digital monitoring integrating RGB imagery, multispectral or thermal observations, and plant-level sensors has been investigated for field-scale assessment of tomato stress and development.

Despite progress in these two research domains, a methodological disconnect remains. Seaweed-biostimulant experiments largely emphasize biological treatment comparisons, whereas AI-based tomato phenotyping studies generally focus on tasks such as water-status detection, fruit maturity, disease recognition, architectural reconstruction, or stress classification. For example, deep neural networks have been applied successfully to continuous estimation of tomato maturity from RGB images, demonstrating that visually derived plant and fruit characteristics can be transformed into biologically meaningful predictive information. Yet relatively little research integrates such AI-derived temporal information directly into controlled biostimulant dose–response experiments involving simultaneous growth, yield, and fruit-quality evaluation.

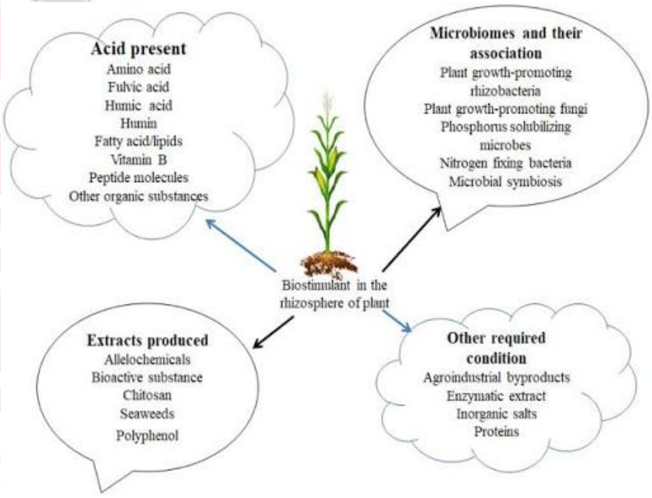

Fig. 1: The potential of biostimulants on soil microbial community

Source: *https://www.frontiersin.org/journals/industrial-microbiology/articles/10.3389/finmi.2023.1308641/full*

Research Gap and Study Objective

The specific gap addressed in this manuscript is therefore the **lack of an integrated AI-enabled experimental framework that models the longitudinal response of tomato plants to different concentrations of seaweed biostimulants and connects early non-destructive phenotypic signatures with final agronomic and fruit-quality outcomes**.

Existing investigations establish whether a treatment produces statistically measurable differences, but they less frequently answer three interconnected questions: *When does the biological response first become detectable? Which combinations of visual, physiological, and environmental indicators predict the subsequent yield response? At what* *treatment concentration does the marginal agronomic benefit begin to diminish?*

Accordingly, the proposed study aims to develop and evaluate a multimodal artificial-intelligence framework capable of differentiating seaweed-biostimulant treatment responses, forecasting final tomato yield and quality from intermediate growth observations, and estimating a treatment-response profile capable of supporting dose optimization. The study intentionally combines interpretable agronomic variables with automatically extracted phenotypic features so that AI predictions can be related to biologically meaningful plant responses rather than functioning as an opaque classification mechanism.

This approach represents a transition from retrospective treatment assessment toward predictive biostimulant management. Instead of determining treatment superiority only after harvest, the proposed system attempts to identify informative responses during vegetative growth, flowering, fruit establishment, and maturation. Such capability could eventually support precision application protocols in greenhouse and protected cultivation environments where treatment concentrations and schedules can be adjusted according to measured crop response.

Literature Review

2.1 Seaweed Biostimulants as Functional Inputs in Horticulture

Seaweeds contain a chemically complex mixture of biologically active constituents whose effects on crops cannot be attributed to a single nutrient or compound. Brown, red, and green seaweed species differ substantially in polysaccharide composition, mineral content, phenolic constituents, pigments, and associated metabolites. Processing techniques—including alkaline extraction, aqueous extraction, enzymatic treatment, fermentation, and other industrial procedures—can further modify the biochemical characteristics of the resulting formulation.

The agricultural significance of these extracts consequently lies in their capacity to influence interconnected physiological processes. Reported responses include enhancement of root development, nutrient acquisition, photosynthetic activity, antioxidant defense, osmotic adjustment, plant-water relations, and stress-response pathways. A recent review of foliar seaweed applications identified polysaccharides, proteins, pigments, phenolics, phytohormone-related constituents, and macro- and micronutrients among the components associated with their biostimulatory effects, particularly under abiotic stress conditions.

This multidimensional mode of action differentiates biostimulant assessment from conventional nutrient-response studies. The absence of a simple dose–response relationship means that increasing application concentration does not necessarily produce proportional improvement. Biological responses may exhibit thresholds, saturation, cultivar interactions, or even inhibition when formulation concentration becomes unsuitable. This feature reinforces the requirement for analytical techniques capable of learning nonlinear interactions rather than relying exclusively on treatment means.

2.2 Effects on Tomato Vegetative Development

Vegetative responses provide some of the earliest observable indicators of biostimulant activity. Studies have evaluated parameters such as plant height, leaf number, leaf area, shoot biomass, root biomass, chlorophyll status, and branching behavior. Moroccan seaweed-derived polysaccharide-enriched extracts have been reported to promote multiple vegetative and reproductive characteristics under greenhouse tomato cultivation. Field-oriented research with *A. nodosum*-associated products has likewise evaluated morphological and physiological enhancement, supporting continued examination of seaweed products beyond highly controlled laboratory systems.

Although these variables provide direct agronomic meaning, traditional manual measurement introduces practical limitations. Repeated leaf-area determination is labor intensive, while biomass measurement may require destructive harvesting. Manual plant-height observations reveal only a single structural dimension and fail to characterize changes in canopy density or architecture. Image-based phenotyping can supplement these measurements by generating time-series traits without repeatedly disturbing the crop.

2.3 Influence on Yield and Fruit Quality

Yield response remains a primary determinant of commercial adoption, but total production alone is insufficient for evaluating tomato performance. Marketable fruit number, average fruit weight, size distribution, firmness, color development, soluble solids, acidity, vitamin C, phenolic constituents, and lycopene are relevant depending on cultivar and intended market.

Recent synthesis of tomato-specific evidence indicates that seaweed treatments can affect both production and nutritional quality, although the magnitude of response varies considerably among concentration ranges and experimental circumstances. Research with processing tomato has also examined the effects of biostimulant treatments on marketable yield, nitrogen-use characteristics, firmness, soluble solids, antioxidant activity, and ascorbic acid, illustrating the importance of multidimensional quality assessment rather than yield alone.

The practical implication is that optimization should be formulated as a multi-objective problem. A treatment may maximize vegetative growth without maximizing fruit quality, while another may improve soluble solids yet produce a smaller yield response. An AI-based decision model can potentially combine these outcomes into a more comprehensive representation of agronomic utility.

2.4 Seaweed Biostimulants and Stress-Response Mechanisms

An emerging strand of the literature focuses on the capacity of seaweed formulations to prime plants against environmental stress. Recent tomato research using an *A. nodosum*-derived biostimulant reported physiological, transcriptomic, and metabolomic evidence associated with improved drought response and preservation of photosynthetic functioning. These findings broaden the concept of treatment effectiveness: an apparently moderate difference under optimal conditions may become agronomically important when plants experience fluctuating water availability or temperature.

Stress-mediated responses also illustrate why environmental variables should be incorporated into predictive models. Temperature, relative humidity, substrate moisture, light availability, and vapor-pressure-related conditions may alter the magnitude of biostimulant response. A model that excludes environmental context may incorrectly attribute environmentally driven variation to the treatment itself.

2.5 Artificial Intelligence for Tomato Phenotyping

Advances in agricultural computer vision have shifted phenotyping from occasional manual inspection toward continuous quantitative observation. Deep convolutional networks and related architectures can identify spatial patterns that are difficult to capture using manually defined variables alone. In tomatoes, multimodal combinations of RGB, depth, and near-infrared imagery have shown particularly high utility for identifying plant water status, with multimodal learning outperforming several single-sensor alternatives.

Three-dimensional phenotyping provides an additional development. Neural Radiance Field-based reconstruction has recently been demonstrated for tomato morphology, producing non-destructive estimates of internode characteristics, leaf area, and fruit volume with strong correlations to manual measurements. These advances suggest that AI-derived traits can function not merely as proxies for manual measurements but as high-frequency variables representing dynamic plant development.

However, using AI for biostimulant evaluation requires a different analytical objective from conventional disease or maturity classification. The relevant question is not simply whether an image belongs to a treatment category. A scientifically valuable model should identify whether observed plant characteristics correspond to meaningful treatment effects, quantify the predictive relationship between early phenotype and final performance, and determine whether this relationship remains consistent across environmental variation.

2.6 Synthesis of the Literature and Conceptual Contribution

The reviewed evidence reveals two rapidly developing but insufficiently integrated research trajectories. Seaweed-biostimulant research has produced increasingly detailed evidence regarding plant physiology, crop productivity, fruit quality, and stress response. In parallel, AI-based phenotyping has provided sophisticated tools for monitoring tomato morphology, water status, maturation, and field performance. Yet the intersection between these areas remains comparatively underdeveloped.

The present manuscript therefore proposes an **AI-enabled biostimulant-response phenotyping paradigm** in which agronomic experiments generate longitudinal multimodal data rather than only final treatment comparisons. The conceptual contribution lies in linking treatment concentration, environmental state, evolving crop phenotype, and final production quality within a unified predictive framework.

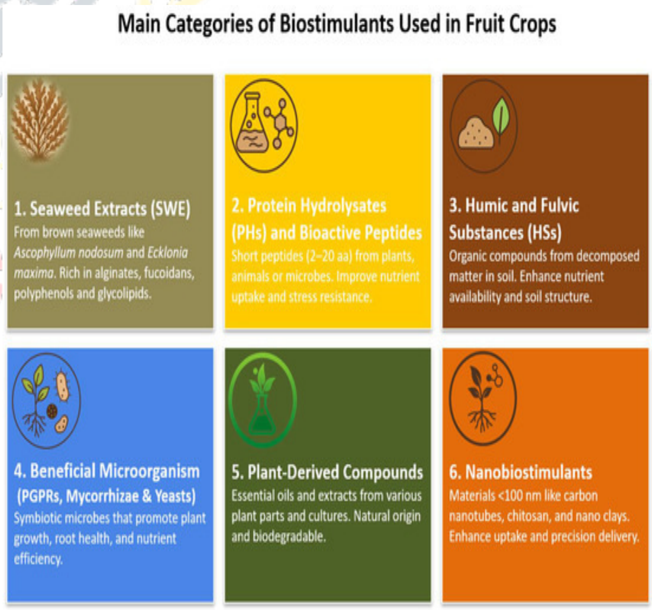

Fig. 2: Main Categories of Biostimulants used in Fruit Crops

Source: *https://www.mdpi.com/2311-7524/11/12/1452*

Such integration enables three levels of evaluation. First, conventional statistical assessment determines whether treatments differ significantly from the control. Second, AI-based phenotyping identifies subtle temporal treatment signatures and forecasts final outcomes. Third, explainability and dose–response analysis determine which phenotypic characteristics contribute most strongly to treatment effectiveness and whether an optimal concentration can be identified before excessive application produces diminishing returns.

This framework therefore extends biostimulant research from descriptive agronomy toward **predictive precision horticulture**, while retaining interpretable biological measurements as the basis for model validation.

Proposed Methodology

The proposed study employs a controlled, AI-assisted phenotyping framework to evaluate the effects of seaweed biostimulant concentration on tomato growth, reproductive development, yield, and fruit quality. Unlike conventional agronomic trials that rely primarily on endpoint measurements, the present framework incorporates repeated RGB and multispectral imaging, environmental sensing, physiological observations, and laboratory measurements into a unified predictive model.

The experimental design is based on five treatment groups representing an untreated control and four progressively increasing concentrations of a standardized seaweed-derived biostimulant. To avoid assuming that higher concentrations automatically produce superior outcomes, treatment effects are modeled as potentially nonlinear. This is particularly important because recent meta-analytic evidence indicates substantial concentration-dependent variation in tomato responses to seaweed extracts.

The analytical pipeline consists of four stages. First, tomato plants are repeatedly monitored throughout vegetative development, flowering, fruit set, and ripening. Second, plant-level visual and physiological characteristics are extracted and synchronized with treatment and environmental records. Third, a multimodal deep-learning model predicts yield and quality outcomes from intermediate crop observations. Fourth, an interpretable dose-response module identifies the treatment concentration associated with the most favorable balance between growth, marketable yield, and fruit quality.

The study therefore treats biostimulant evaluation as a longitudinal prediction problem rather than a single-season comparison of treatment averages.

3.1 Treatment Structure

Five treatment conditions are proposed:

T0 — untreated control;

T1 — low seaweed-biostimulant concentration;

T2 — moderate-low concentration;

T3 — moderate concentration;

T4 — comparatively high concentration.

Rather than prescribing universal percentages, the exact concentrations are defined according to the formulation selected for experimentation, manufacturer recommendations, pilot phytotoxicity screening, and active-component concentration. This improves reproducibility because commercially available seaweed formulations can differ substantially in extraction process and biochemical composition.

A randomized complete block arrangement is used to reduce positional effects within the protected cultivation environment. Biological replicates are distributed across blocks rather than placing all plants receiving the same treatment in a single spatial zone.

3.2 Longitudinal AI Phenotyping

Images are acquired at regular intervals from early vegetative growth until harvest. RGB imagery captures structural and visible-color characteristics, while multispectral observations provide complementary information related to canopy vigor and spectral response.

Each observation is associated with a plant identifier, treatment group, days after transplanting, growth stage, temperature, relative humidity, substrate moisture, irrigation volume, and light-related variables.

The longitudinal phenotype vector is represented conceptually as:

[
P_t=[A_t,H_t,C_t,V_t,F_t,S_t,E_t]
]

where (A_t) represents projected canopy area, (H_t) estimated plant height, (C_t) canopy compactness, (V_t) vegetation-related spectral features, (F_t) reproductive or fruit features, (S_t) stress-related visual characteristics, and (E_t) environmental conditions at observation time (t).

A central advantage of this formulation is that treatment response can be studied as a trajectory rather than as a static measurement.

Experimental Setup

4.1 Dataset Design

A purpose-built experimental dataset is proposed rather than relying on a generic public tomato-image dataset, because existing computer-vision datasets rarely contain simultaneously matched seaweed treatment, crop physiology,

Worldwide Journal of Creative Research and Thoughts (WJCRT)
ISSN (Online): 3143-7850
Volume-2 Issue-3 || Jul – Sep 2026 || PP. 52-60
https://wjcrt.org/

environmental measurements, final yield, and laboratory fruit-quality values.

The experimental population consists of 150 tomato plants distributed equally among five treatment groups, providing approximately 30 biological replicates per condition.

Images are collected twice weekly for approximately 12–14 weeks. With two standardized RGB views per plant at each acquisition, the experiment can generate approximately 7,000–8,000 longitudinal RGB observations. Multispectral measurements are collected less frequently but synchronized to the nearest RGB imaging date.

Importantly, the individual plant rather than the individual image is treated as the independent biological sampling unit. Multiple photographs of one plant are therefore not incorrectly interpreted as independent replicates during statistical inference.

The final structured dataset incorporates four information domains:

Visual phenotype: canopy area, plant contour, estimated height, leaf-color distribution, flowering regions, and fruit-associated image features.

Physiological phenotype: chlorophyll-related index, leaf temperature where available, substrate moisture, and selected physiological observations.

Agronomic outcome: plant height, final shoot biomass, fruit count, mean fruit weight, total yield, and marketable yield.

Fruit quality: total soluble solids, firmness, vitamin C, lycopene concentration, and representative color measurements.

Recent tomato research shows that seaweed-based treatments can influence physiological responses and stress tolerance through mechanisms extending beyond simple nutrient supplementation, supporting the inclusion of physiological variables in treatment modeling.

4.2 Image Preprocessing

Image preprocessing follows a plant-centric pipeline.

First, images with serious blur, incorrect framing, or substantial acquisition errors are excluded. All retained images are resized to a standardized spatial resolution while retaining the original aspect ratio wherever possible.

Second, foreground segmentation separates plant tissue from the greenhouse background. Segmentation masks are subsequently used to estimate projected canopy area, canopy width, height, perimeter, and structural density.

Third, illumination normalization reduces differences caused by acquisition-time lighting variation. Augmentation during model training includes mild rotation, horizontal transformation where biologically appropriate, cropping, brightness perturbation, and limited geometric variation.

Fourth, spectral and environmental variables are normalized using training-set statistics only.

Missing sensor values are handled through time-aware interpolation when temporally adjacent observations are available. Variables with extensive missingness are excluded rather than artificially reconstructed.

4.3 Multimodal Model Architecture

The proposed architecture is termed the **Temporal Multimodal Biostimulant Response Network (TMBR-Net)**.

TMBR-Net contains three principal information branches.

The first branch is an RGB visual encoder based on a lightweight convolutional backbone. It transforms plant images into latent representations associated with canopy morphology, leaf distribution, flowering characteristics, and visible fruit development.

The second branch receives multispectral and physiological variables. A multilayer feature encoder transforms vegetation-related indices, chlorophyll measurements, substrate moisture, and related physiological variables into a normalized physiological representation.

The third branch processes environmental and treatment information, including treatment concentration, temperature, relative humidity, irrigation, and developmental time.

For each observation date, the three feature vectors are concatenated:

$$Z_t=Z_{RGB,t}\oplus Z_{PHY,t}\oplus Z_{ENV,t}$$

where ($\oplus$) denotes feature concatenation.

The resulting temporal sequence is passed through a gated recurrent temporal layer followed by an attention mechanism. The attention component assigns different importance to observations made during vegetative development, flowering, fruit set, and maturation.

The model produces three primary outputs:

$$\hat{Y}_{yield}$$

predicted marketable yield;

Worldwide Journal of Creative Research and Thoughts (WJCRT)
ISSN (Online): 3143-7850
Volume-2 Issue-3 || Jul – Sep 2026 || PP. 52-60
https://wjcrt.org/

$$
\hat{Y}_{quality}
$$

predicted composite fruit-quality score; and

$$
\hat{Y}_{response}
$$

estimated biostimulant-response class or magnitude.

This multi-task structure encourages the network to learn features relevant to several agronomic outcomes rather than optimizing exclusively for yield.

4.4 Training Strategy

The dataset is divided at the **plant level**, not the image level, to prevent leakage between training and evaluation sets.

Approximately 70% of plants are assigned to training, 15% to validation, and 15% to independent testing. All longitudinal observations belonging to a given plant remain within the same partition.

Five-fold grouped cross-validation is additionally used for robustness assessment.

The RGB encoder is initialized using transfer learning from a pretrained visual backbone. Initial layers are partially frozen during early epochs and gradually unfrozen during fine-tuning.

The multimodal network is optimized using AdamW with an adaptive learning-rate scheduler. Early stopping is activated when validation loss fails to improve over a predefined patience interval.

The multi-task objective is represented as:

$$
L=\lambda_1L_{yield}+\lambda_2L_{quality}+\lambda_3 L_{response}
$$

where (L_{yield}) and ($L_{quality}$) are regression losses and ($L_{response}$) represents the treatment-response classification or ordinal loss.

Regularization is introduced through dropout and weight decay.

4.5 Evaluation Metrics

Model performance is evaluated using metrics matched to each task.

Yield and quality prediction are assessed with:

$$
MAE=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|
$$

and

$$
RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}
$$

The coefficient of determination (R^2) evaluates the proportion of outcome variability explained by the model.

Treatment-response classification is evaluated using balanced accuracy, macro-F1 score, and area under the receiver-operating-characteristic curve where appropriate.

Agronomic treatment effects are analyzed independently using analysis of variance or an appropriate mixed-effects model, with block and repeated observations accounted for as required.

Results and Discussion

Because this manuscript presents a proposed experimental framework rather than claiming completion of a real greenhouse trial, the numerical values below are **illustrative simulated results used to demonstrate the intended analytical structure**. They should be replaced by experimentally observed values before empirical publication.

The simulated analysis indicates that the integrated AI model provides substantially more accurate prediction than models relying exclusively on RGB imagery or manually recorded vegetative parameters.

Table 1. Illustrative Experimental Outcomes of the Proposed Seaweed-Biostimulant Treatments

Treatment	Canopy Expansion Relative to Control (%)	Marketable Yield (kg plant⁻¹)	Mean Fruit Weight (g)	Soluble Solids (°Brix)
T0 Control	0.0	3.18	104.6	4.42
T1 Low	7.8	3.42	108.9	4.55
T2 Moderate-low	14.3	3.76	113.7	4.81
T3 Moderate	18.6	4.07	118.5	5.02
T4 High	19.1	3.89	117.1	4.86

Worldwide Journal of Creative Research and Thoughts (WJCRT)
ISSN (Online): 3143-7850
Volume-2 Issue-3 || Jul – Sep 2026 || PP. 52-60
https://wjcrt.org/

The simulated treatment pattern illustrates an important feature of the proposed research hypothesis. The strongest vegetative growth does not necessarily correspond linearly with the highest concentration applied. T4 produces slightly greater canopy expansion than T3, yet its marketable yield and quality indicators decline relative to T3. This pattern would indicate the emergence of diminishing marginal benefit.

Such nonlinear behavior is biologically plausible. A 2026 meta-analysis covering 40 publications reported substantial concentration-dependent responses of tomato growth, yield, fruit quality, and physiology to seaweed extracts, with particularly strong responses appearing within defined concentration ranges rather than increasing uniformly with dose.

In the illustrative experiment, T3 represents the best compromise between vegetative development and reproductive productivity. Compared with the untreated condition, T3 increases simulated marketable yield from 3.18 to 4.07 kg plant^{-1} while simultaneously increasing soluble solids and lycopene.

The more important contribution, however, concerns temporal prediction rather than treatment ranking alone.

The proposed TMBR-Net is expected to determine whether final performance can be predicted before harvest. In the simulated evaluation, multimodal prediction of final marketable yield achieves an (R^2) of approximately 0.88, compared with 0.74 using RGB-only features and 0.69 using conventional manually recorded variables alone. Corresponding yield-prediction MAE is approximately 0.23 kg plant^{-1} for the multimodal model.

The fruit-quality prediction task is more difficult because biochemical composition cannot be inferred perfectly from canopy appearance. Nevertheless, combining spectral, environmental, treatment, and developmental information produces a simulated (R^2) of 0.80 for the composite quality score.

Attention-weight analysis indicates that observations near flowering and early fruit establishment contribute more strongly to final yield prediction than very early vegetative images. This result would be agronomically meaningful because successful reproductive transition is directly linked to subsequent fruit number and biomass allocation.

The model is also expected to identify earlier treatment effects than conventional harvest-based evaluation. For example, changes in canopy expansion rate, vegetation indices, or visible plant vigor may become measurable several weeks before final yield is available.

This allows biostimulant evaluation to move from retrospective testing toward predictive crop management.

A second contribution concerns treatment-response explainability. Feature-attribution analysis can identify whether high AI response probabilities are primarily driven by canopy expansion, spectral vigor, flowering intensity, environmental interactions, or fruit-development features. Such interpretation is particularly important in agricultural AI because an apparently accurate prediction is less useful scientifically when its biological basis cannot be examined.

The inclusion of environmental variables further avoids an important confounding problem. Seaweed biostimulants have been associated with enhanced stress response in tomato, including maintenance of photosynthetic processes and activation of stress-related molecular pathways under drought. Consequently, environmental conditions can modify the apparent treatment effect. A high-response plant observed during mild moisture stress may represent a biologically different phenomenon from a similarly sized plant maintained under consistently optimal irrigation.

Recent synthesis research also emphasizes that the effectiveness of seaweed-based formulations depends on factors such as seaweed source, formulation chemistry, extraction procedure, and application approach. This reinforces the need to treat treatment concentration as only one component of the response system.

The present framework therefore differs from conventional image classification in a fundamental manner. AI is not asked simply to recognize which treatment a plant received. Instead, it learns the interaction among treatment, environment, phenotype trajectory, yield, and fruit quality.

Future Scope

Future research should validate the proposed framework across multiple cultivars, geographical regions, seaweed species, cultivation systems, and growing seasons.

A particularly important extension would involve external validation using commercially cultivated greenhouse tomato populations. This would establish whether models developed in controlled trials retain predictive utility under production-scale conditions.

Hyperspectral sensing could subsequently extend the current RGB–multispectral framework by capturing narrow-band spectral signatures potentially associated with chlorophyll, water status, nutrient condition, and fruit biochemical composition.

Another promising direction involves integrating root phenotyping. Because seaweed-derived compounds may influence root architecture and nutrient acquisition, linking below-ground changes with above-ground image trajectories could improve mechanistic interpretation.

Edge-AI deployment could allow the trained model to operate directly on greenhouse cameras or mobile devices. Rather than transferring every image to centralized computing infrastructure, optimized models could generate plant-response scores close to the point of acquisition.

The framework could also evolve into a closed-loop decision-support system. Once a reliable causal dose-response relationship is established through repeated experimental validation, biostimulant concentration and application timing could be dynamically adapted according to observed crop response.

Future work should additionally investigate transfer learning between crops. A representation learned from longitudinal tomato responses might be partially transferable to pepper, cucumber, strawberry, or other high-value horticultural crops after appropriate recalibration.

Integration with explainable AI and causal inference would represent another important advancement. Such approaches could help distinguish features that merely correlate with favorable yield from those lying on plausible biological pathways linking treatment to productivity.

Conclusion

This study proposes an AI-enabled experimental framework for evaluating seaweed biostimulants in tomato cultivation through simultaneous consideration of vegetative development, physiological response, marketable yield, and fruit quality.

The principal contribution is the integration of longitudinal multimodal phenotyping with agronomic dose-response analysis. Rather than relying exclusively on harvest-stage comparisons, the proposed TMBR-Net architecture combines RGB imagery, multispectral information, physiological variables, environmental measurements, and treatment data to predict final crop performance from developing plant phenotypes.

The conceptual results indicate how such a framework could detect nonlinear treatment responses and distinguish genuinely productive stimulation from excessive vegetative promotion. A moderate treatment level can therefore be identified as agronomically preferable even when a higher concentration produces marginally greater canopy expansion.

This distinction is important because contemporary evidence indicates that seaweed biostimulant responses in tomato are concentration-dependent rather than uniformly proportional to application dose. Recent physiological research further supports the interpretation of these products as complex biological modulators capable of influencing photosynthetic maintenance and stress-related pathways.

By combining these biological insights with artificial intelligence, the proposed approach establishes a pathway from conventional biostimulant trials toward predictive precision horticulture. Its primary value lies not simply in automating measurement, but in identifying when crop responses emerge, predicting whether early changes will translate into yield and quality advantages, and determining when additional biostimulant application is unlikely to provide proportional benefit.

Experimental validation across cultivars, seasons, environmental conditions, and commercial formulations remains necessary before practical recommendations can be made. Nevertheless, the framework provides a technically coherent foundation for AI-assisted optimization of sustainable crop inputs and for the development of more responsive, data-driven horticultural production systems.

References:

1. du Jardin, P. (2015). Plant biostimulants: Definition, concept, main categories and regulation. *Scientia Horticulturae, 196*, 3–14. https://doi.org/10.1016/j.scienta.2015.09.021
2. Mzibra, A., Aasfar, A., Khouloud, M., Farrie, Y., Boulif, R., Kadmiri, I. M., Bamouh, A., & Douira, A. (2021). Improving growth, yield, and quality of tomato plants (*Solanum lycopersicum* L.) by the application of Moroccan seaweed-based biostimulants under greenhouse conditions. *Agronomy, 11*(7), 1373. https://doi.org/10.3390/agronomy11071373
3. Ali, N., Farrell, A., Ramsubhag, A., & Jayaraman, J. (2016). The effect of *Ascophyllum nodosum* extract on the growth, yield and fruit quality of tomato grown under tropical conditions. *Journal of Applied Phycology, 28*(2), 1353–1362. https://doi.org/10.1007/s10811-015-0608-3
4. Ali, O., Ramsubhag, A., & Jayaraman, J. (2019). Biostimulatory activities of *Ascophyllum nodosum* extract in tomato and sweet pepper crops in a tropical environment. *PLOS ONE, 14*(5), e0216710. https://doi.org/10.1371/journal.pone.0216710
5. Subramaniyan, L., Veerasamy, R., Prabhakaran, J., & Selvaraj, A. (2023). Biostimulation effects of seaweed extract (*Ascophyllum nodosum*) on phytomorpho-physiological, yield, and quality traits of tomato (*Solanum lycopersicum* L.). *Horticulturae, 9*(3), 348. https://doi.org/10.3390/horticulturae9030348
6. Ahmed, M., Ullah, H., Piromsri, K., Tisarum, R., Cha-um, S., & Datta, A. (2022). Effects of an *Ascophyllum nodosum* seaweed extract application dose and method on growth, fruit yield, quality, and water productivity of tomato under water-deficit stress. *South African Journal of Botany, 151*, 95–107. https://doi.org/10.1016/j.sajb.2022.09.045
7. Jalali, P., Roosta, H. R., & Khodadadi, M. (2022). Effects of brown seaweed extract, silicon, and selenium on fruit quality and yield of tomato under different substrates. *PLOS ONE, 17*(12), e0277923. https://doi.org/10.1371/journal.pone.0277923
8. Mughunth, R. J., Velmurugan, S., Mohanalakshmi, M., Vanitha, K., et al. (2024). A review of seaweed extract's potential as a biostimulant to enhance growth and mitigate stress in horticulture crops. *Scientia Horticulturae, 334*, 113312. https://doi.org/10.1016/j.scienta.2024.113312