RESEARCH PAPER

Integrating Organic Fertilized Coco Peat Bricks with Bayesian Generalized Logistic Regression Model for Maximizing Plant Growth Efficiency and Yield

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Abstract

Modern agriculture is increasingly challenged to meet rising food demands while preserving soil fertility and environmental balance. The excessive reliance on chemical fertilizers has resulted in adverse effects such as soil degradation, nutrient imbalance, water contamination and ecological disruption. The excessive use of chemical fertilizers in agriculture has led to soil degradation, environmental pollution and reduced crop sustainability, necessitating eco-friendly alternatives. This study presents a sustainable approach for enhancing plant growth using organic fertilized coco peat bricks integrated with Bayesian Generalized Logistic Regression Model (CPB-BGLR-PGEY). Initially, plants are cultivated using the prepared coco peat medium and data collection is performed by capturing plant images and recording growth parameters such as plant height, leaf count and soil moisture. The collected data is fed to preprocessing technique, which is used to resizing image, noise removal and normalization to improve data quality. Then, Bayesian Generalized Logistic Regression Model (BGLR) is employed to analyze plant images for classification of plant health and prediction of growth performance. BGLR does not indicate any adaptation of Supercell Thunderstorm Algorithm (STA) that ensures accurate classification of plant health and prediction of growth by determining optimal parameters. Therefore, STA technique is used to enhance hyper parameter tuning of BGLR method, which precisely classifies the plant growth. The efficiency of the proposed approach is evaluated using a number of performance criteria including Accuracy, Precision, Recall, Specificity, F1-score, Receiver Operating Characteristic (ROC) and Computational Time are analyzed. The proposed CPB-BGLR-PGEY approach attains 99.43% accuracy and 98.14% precision compared with existing techniques. The results demonstrate improved plant productivity and provide a reliable, data-driven solution for sustainable and intelligent agriculture.

Keywords: *Coco Peat Bricks, Organic Fertilizer, Bayesian Generalized Logistic Regression Model, Supercell Thunderstorm Algorithm, Sustainable Agriculture.*

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1. Introduction

Agriculture is essential for sustaining human life by ensuring food security and supporting economic growth. [1-2]. Although these inputs have boosted crop yields, their overuse has resulted in soil degradation, reduced microbial activity, water contamination and declining long-term soil fertility. These concerns emphasize the urgent need for sustainable and environmentally friendly agricultural practices [3-4]. In recent years, organic farming practices have gained significant attention as a sustainable alternative to conventional agricultural methods [5-6]. Among various organic materials, coco peat has emerged as a promising growing medium due to its physical and chemical properties. Coco peat, also known as coir pith is a by-product of coconut husk processing and is widely available in tropical regions. It is lightweight, biodegradable and possesses excellent water retention and aeration capabilities making it highly suitable for plant growth [7-8].When enriched with organic fertilizers and beneficial microorganisms, coco peat transforms into a nutrient-rich medium that effectively supports plant development [9]. The coco peat is converted into compressed bricks enhances its practicality by improving ease of transportation, storage and handling. Upon hydration, these bricks expand significantly, forming a loose and porous structure that promotes strong root growth and improves overall soil texture [10].

Modern agriculture is facing serious challenges due to the excessive use of chemical fertilizers, which leads to soil degradation and reduced fertility .Continuous use of synthetic inputs reduces beneficial microbial activity and pollutes water. Conventional soils frequently lack water retention and aeration resulting in inefficient nutrient utilization. There is a scarcity of environmentally friendly and biodegradable growing material. Handling and transportation of traditional substrates are also difficult.

The novelty of this research lies in the integrated framework that combines eco-friendly organic fertilized coco peat brick cultivation with a BGLR model for intelligent plant growth prediction. This approach effectively captures both visual and physiological plant features through image-based analysis and growth parameter monitoring, enabling accurate classification and prediction of plant health. The STA technique enhances the BGLR model by providing efficient hyperparameter tuning through dynamic exploration and exploitation mechanisms improving convergence speed and predictive accuracy. This unified system offers a scalable, adaptive and high-performance solution for sustainable agricultural analytics enabling precise plant monitoring, improved productivity and environmentally responsible farming in modern precision agriculture environments.

Major contribution of this paper includes,

- The goal of this research is to develop a CPB-BGLR-PGEY model for sustainable plant growth enhancement, accurate plant health classification, growth prediction and intelligent decision-making using eco-friendly cultivation and data-driven analysis.
- It collects plant dataset including images and growth parameters such as plant height, leaf count and soil moisture, and utilizes this data to enable accurate analysis, classification and prediction of plant growth performance.
- It applies preprocessing techniques such as image resizing, noise removal and normalization to enhance data quality and ensure accurate and reliable plant growth analysis and prediction.
- It employs a deep learning-based BGLR model to effectively analyze plant images and growth parameters for accurate plant health classification and growth prediction by capturing complex patterns and relationships in the data.
- It utilizes the STA technique to perform efficient hyperparameter tuning of the BGLR model, improving convergence speed, classification accuracy and overall prediction performance.

2. Material and Methods

2.1 Coco peat

Coco peat is a natural, soil-like growing medium derived from coconut husk. It is widely used for its excellent water retention capacity and ability to support plant growth. The materials used are organic coco peat, normal coco peat, soil, plant seeds, pots/containers, water and fertilizers. Organic coco peat is processed and contains low salt content, whereas normal coco peat may contain higher salt levels and requires washing before use. Initially, both types of coco peat were prepared. The normal coco peat was soaked in water and thoroughly washed to remove excess salts, while the organic coco peat was used directly. The coco peat was then mixed with soil in equal proportions to prepare the growing medium. The prepared mixtures were filled into pots and seeds were sown uniformly. The plants were watered regularly and maintained under suitable environmental conditions including adequate sunlight and temperature. Plant growth parameters such as germination rate, plant height and overall plant health were observed and recorded over a specific period. The growth performance of plants cultivated using organic coco peat was compared with those grown using normal coco peat to evaluate their effectiveness as growing media.

2.2 Soil

Soil is the natural material found on the surface of the earth that supports plant growth**.** In this experiment, the basic growing media is soil. It gives plants the essential nutrients, nourishment, water and air they need to grow. The soil should be ideal for planting, clear of stones and dirt. The dirt was collected and filtered to eliminate impurities like stones and unwanted particles. It was then combined with coco peat in a pre-determined ratio to promote water retention and aeration. Before the seeds were planted, the prepared mixture was placed in pots.

2.3 Seeds

Seeds are small parts of a plant that can grow into a new plant. Seeds are used as the planting medium in this experiment. They are chosen based on their uniform size and quality to enable good germination and growth. Healthy seeds were selected and evenly distributed in pots holding the prepared soil and coco peat mixture. To facilitate germination, the seeds were covered with a thin layer of growth material and watered on a regular basis.

2.4 Fertilizers

Fertilizers were added to provide essential nutrients and promote plant growth. Fertilizers were used to provide vital nutrients for plant growth because coco peat has a low natural nutrient content. A proper amount of fertilizer was applied at regular intervals to promote healthy plant growth.

3. Literature Survey

Several studies were previously submitted with coco peat bricks utilizing deep learning; some works were reviewed here,

In 2025, Parvathi, L., *et.al*, [11] have suggested Sustainable Herbo-foam concrete with soap nut and coco-peat: properties and thermal modelling. The advantages of foam concrete include its lightweight nature, excellent workability, and strong thermal resistance, making it ideal for insulation and partition walls. Foam concrete was created using synthetic and natural foaming chemicals, with sand substituted by treated coco-peat. Soap nut extract was used as a natural foaming agent, while coco-peat was treated with NaOH to improve compatibility.

In 2023, Singh, A.K., *et.al*, [12] have introduced Influence of potting media composition on quality flower production of petunia (Petunia hybrida). The purpose of the study was to evaluate different growing media combinations containing coco peat, vermicompost, FYM, leaf mold, perlite and vermiculite in various ratios to identify the most suitable medium for enhancing vegetative growth, root development, and flowering quality of petunia plants.

In 2025, Basyal, P., *et.al*, [13] have introduced Micropropagation and genetic homogeneity assessment of Curcuma aeruginosa Roxb. The advantage of the study was to create an efficient Micropropagation protocol for Curcuma aeruginosa using rhizome bud explants, as well as to assess the genetic stability of the regenerated plants using molecular markers, in order to support large-scale propagation, conservation, and potential commercial cultivation.

In 2023, Mamatha, V., *et.al*, [14] have introduced Machine learning based crop growth management in greenhouse environment using hydroponics farming techniques. The purpose of this research was to create an automated smart greenhouse hydroponics system that uses coconut coir as a sustainable growing medium, optimize environmental conditions for efficient crop production and use machine learning techniques to model and predict the growth of leafy vegetables under different conditions.

In 2024, Lu B *et.al,* [15] have introduced Rapid and high-performance analysis of total nitrogen in coco-peat substrate by coupling laser-induced breakdown spectroscopy with multi-chemometrics The goal of this research was to create a rapid and accurate method for determining total nitrogen content in coco-peat substrate using laser-induced breakdown spectroscopy (LIBS) combined with advanced variable selection and regression techniques to aid in precise nutrient assessment and fertilization management.

Table 1: Comparison of Literature Survey

Author & Ref	Objective	Model	Advantages	Limitations
Parvathi L et al. (2025) [11]	Develop eco-friendly foam concrete using coco peat	Herbo-foam concrete	Sustainable; good thermal properties	Lower strength; complex processing
Singh A.K et al. (2023) [12]	Improve petunia growth using coco peat media	Potting mix combinations	Better growth and flowering	Needs ratio optimization
Basyal P et al. (2025) [13]	Micropropagation and genetic stability of C. aeruginosa	In vitro + molecular markers	Mass propagation; uniform plants	High cost; lab setup needed
Mamatha V & Kavitha J.C (2023) [14]	Smart hydroponics using coconut coir	ML-based greenhouse (KNN)	Automation; faster growth	High setup cost
Lu B	Detect	LIBS +	Fast	Expens

et al. (2024) [15]	nitrogen in coco-peat	PLSR	and accurate analysis	ive equipment

Table 1 covers recent research on coco peat-based applications, emphasizing significant advances in sustainable material creation, improved plant growth medium, micropropagation techniques, smart hydroponic systems, and advanced nutrient monitoring technologies. These approaches increase heat efficiency, plant growth performance, uniform propagation, agricultural automation and nutrient analysis accuracy. They are frequently hindered by expensive production and setup costs, complex processing requirements, the need for exact optimization, and limited scalability for large-scale deployment. Therefore, this research focuses on resolving these limitations by offering a cost-effective, efficient and scalable approach that improves performance, simplifies processing, and ensures long-term and practical applicability in agricultural systems.

4. Methodology

The proposed CPB-BGLR-PGEY approach makes use of data acquired from plant growth environments. The whole framework consists of data acquisition; preprocessing techniques such as image resizing, noise removal and normalization followed by optimum model training and evaluation. The BGLR model uses these characteristics to assess plant health and predict growth performance, while the STA technique improves hyperparameter tuning for greater classification accuracy and prediction efficiency. Figure 1 depicts the proposed system architecture and comprehensive explanations are provided in the following subsections.

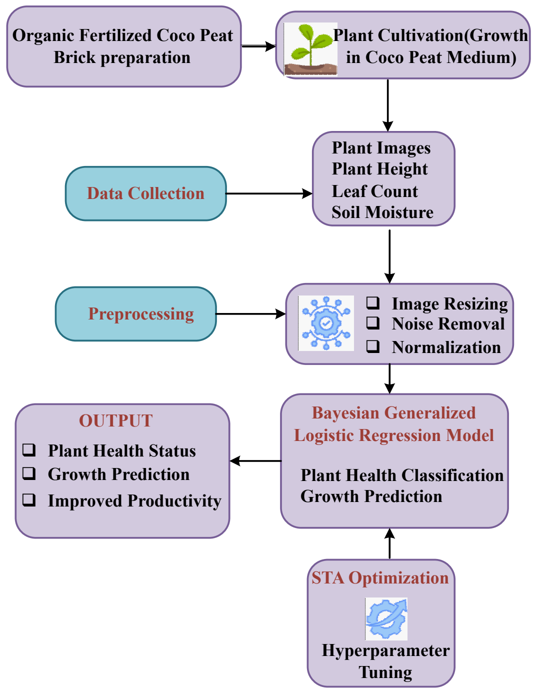

Figure 1: Block diagram of proposed CPB-BGLR-PGEY method

4.1 Data Acquisition

During this stage, plant growth data is carefully collected from plants grown in an organic fertilized coco peat brick media. The data collection method includes taking high-resolution photos of plants at regular growth intervals with digital cameras or imaging equipment, as well as documenting crucial physiological and environmental factors such as plant height, number of leaves, and soil moisture levels. These measures provide both visual and numerical information about the health and development of the plants. The acquired data is recorded in a structured dataset, which is then used as the primary input for the proposed model's preprocessing and analysis. By combining image-based observations with quantitative growth measurements, the data acquisition stage guarantees that plant growth circumstances are accurately represented for categorization and prediction.

4.2 Pre-processing

The pre-processing stage deals with the plant images and associated growth parameters obtained from the coco peat-based farming system. This stage enhances data quality by utilizing resizing, noise removal and normalizing techniques to provide dependable model training and accurate plant growth prediction.

Image Resizing

Plant images are scaled to a predetermined spatial resolution to maintain consistent input dimensions. This phase decreases computational complexity and allows for efficient batch-wise processing during training while keeping important structural information about plant leaves and stems.

Noise Removal

Noise removal is used to remove undesired distortions induced by lighting changes, sensor noise and environmental factors. This improves image clarity and increases the accuracy of feature extraction for plant health categorization and growth prediction.

Intensity Normalization:

Plant image intensities are inconsistent due to variations in illumination, camera settings, and environmental influences. Intensity normalization is used to rescale pixel values to a standard range. This increases contrast constancy across images, improves feature representation, and enables robust model training. The intensity normalization is given in equation (1).

$$I_{norm} = \frac{I - \mu_I}{\sigma_I}$$

(1)

Here, μ_I denotes the mean of image intensities, σ_I denotes the standard deviation and I denotes the input plant image.

4.3 Fertilized Coco Peat Bricks using Bayesian generalized logistic regression model (BGLR)

In this section, Fertilized Coco Peat Bricks using BGLR [16] is discussed. BGLR employed to analyze plant images for classification of plant health and prediction of growth performance. BGLR offers various advantages for evaluating plant images in order to classify plant health and predict growth performance in a fertilized coco peat brick system. It provides probabilistic predictions, allowing for not only class labels but also confidence measures, which improves the dependability and interpretability of outcomes. The model effectively manages uncertainty in agricultural data induced by differences in lighting, soil moisture, and plant development conditions, making it ideal for real-world farming scenarios. By combining Bayesian inference, BGLR increases learning stability and performance even with small or noisy datasets. It also shows good generalization across multiple growth phases and environmental variables, resulting in constant forecast accuracy. Initialize the BGLR model by assigning prior probability distributions to all model parameters to incorporate prior knowledge and ensure probabilistic learning as given in equation (2).

$$\varphi = (x_i'; \beta, \beta', \alpha)$$

(2)

Where, φ is the complete parameter vector of the model, x_i' is the input variables, α is the additional model parameter, β is the set of mean regression coefficients and β' is the set of variance regression coefficients. Apply Bayesian updating to integrate prior knowledge with observed plant image data, producing posterior probability distributions for accurate classification of plant health classes. Thus, it is given in equation (3).

$$f_{post}(\varphi|x') \alpha f_{like}(x'|\varphi) f_{prior}(\varphi)$$

(3)

Where, f_{post} represents the probability of observing the plant image data given the model parameters, $f_{like}(x'|\varphi)$ is the Likelihood function and $f_{prior}(\varphi)$ is the Prior distribution of parameters. Optimize the BGLR model parameters to maximize classification accuracy and ensure stable and reliable prediction performance as given in equation (4).

$$\beta_p' \sim N\{\mu_{normal}^{(t-1)}, \sigma_{normal}^2\}$$

(4)

Where, β_p' are the number of parameters in each vector space β and β'. β_p , β_p' is the Individual regression coefficients, N is the Normal distribution, μ_{normal} is the mean of the prior distribution, σ_{normal}^2 is the Variance of the prior distribution and p is the Number of parameters. Classify plant health state into categories such as healthy, unhealthy, and mild stress and then estimate plant growth performance using the model probabilistic output score. Thus, it is given in equation (5)

$$X_i = \beta_0 + \beta_1 y_i + \in_i$$

(5)

Where, X_i stands for the possible classification categories of plant condition, β_0 is the Intercept or constant term, β_1 is the regression coefficients and $\in_i$ is the error term or random noise. Finally, the BGLR model successfully analyzes plant images for plant health classification and growth performance prediction. STA is utilized to optimize the hyperparameters of the BGLR model for improved performance and accuracy.

4.4 Optimization using Supercell thunderstorm algorithm (STA)

In this section, optimization using STA [17] is discussed. STA is used to enhance hyper parameter tuning of BGLR method, which precisely classifies the plant growth. The STA provides several advantages when used for hyperparameter tuning of the BGLR in plant growth classification using deep learning-based fertilized coco peat bricks. One of its primary advantages is its powerful global search capabilities, which effectively explores the whole hyperparameter space while reducing the risk of becoming caught in local optima. STA also ensures a balanced exploration and exploitation strategy, allowing the model to simultaneously seek for new regions and refine the best solutions for maximum performance. Another significant advantage is its capacity to achieve rapid convergence, which shortens computational time while increasing model efficiency. STA improves the accuracy and stability of BGLR by identifying the best hyperparameters for plant health and growth prediction.

Step 1: Initialization

The STA approach simulates the activity of Supercell thunderstorms. The algorithm can be divided into three parts: spiral motion, formation and jet stream. STA, like most metaheuristic, is based on population data. The initial trial involves uniformly distributing starting solutions over the search space and it is given in equation (6).

$$Y_i = lb + r_1(ub - lb) \quad , \quad i = 1,2,....n \tag{6}$$

Where, lb and ub are the lower and upper bounds of the search space respectively, r_1 is a random vector which is uniformly distributed in the interval [0, 1]and n is the number of storm populations.

Step 2: Random Generation

Following setup, random factors are created for the input. It is dependent upon an explicit hyper parameter requirement.

Step 3: Fitness Function

Create input parameter at random after initialization. Parameter optimization is used in its computation. It is expressed in equation (7).

$$Fitness\ Function = Optimizing\ [Hyperparameter] \tag{7}$$

Step 4: Spiral motion

Supercell thunderstorms have distinct rotation patterns and often resemble mesocyclone. This rotation is analogous to spiraling motion seen in natural phenomena like hurricanes and tornadoes .The STA simulates the spiral motion of a storm using mathematical models and it is given in equation (8).

$$s = e^3 + (1 - a).\frac{t}{t_{max}} \tag{8}$$

Where, a denotes control coefficient. The control coefficient is a random value that ranges from 0 to 1 as the iteration increases. The constant control allows storms to follow the optimal and preceding people throughout the first stage t denotes the current iteration, while t_{max} represents the maximum number of iterations.

Step 5: Tornado formation

One of the most damaging elements of Supercell thunderstorms is their capacity to generate tornadoes. Tornadoes are strong windstorms that originate in a super cell's revolving updraft .STA tries to replicate tornado development in Supercell using its algorithms. This allows meteorologists to better estimate when and where tornadoes may develop within a storm. Tornadoes significantly disrupt Supercell thunderstorms. Population positions are changed based on tornado formation to avoid falling into local optimal solutions. It is given in equation (9).

$$G_2 = 2 \times n \times \left(0.1 - 0.05.\frac{t}{t_{max}}\right) \tag{9}$$

Where, n is the number of storm population.

Step 4: Jet stream

The jetstream is a high-speed, narrow air current that exists in the higher regions of the Earth's atmosphere. It plays a critical role in weather patterns, influencing the formation and migration of violent thunderstorms including supercells. STA considers the jet stream's influence on supercell thunderstorms as its interaction with the storm can significantly affect their genesis, evolution and trajectory. During this phase, storms prepare to strike the ideal place inside the search region with all other points converging on it and it is given in equation (10).

$$d_1\ (i)= \frac{dr(i)}{max(|dr|)} \tag{10}$$

Where , d_1 (i) is the normalized value of $dr(i)$, $dr(i)$ is the original data value at index i, $max(|dr|)$ is the maximum absolute value in the dataset dr and i is the index of the data point. It is given in equation (11).

$$x_1\ (i)= \frac{xr(i)}{\max(|yr|)} \tag{11}$$

Where, x_1(i) is the normalized value of $xr(i)$, $xr(i)$ is the original data value at index i, $\max(|yr|)$ is the maximum absolute value in the dataset dr and i is the index of the data point.

Step 5: Exploration stage

Storms are randomly initiated and travel in a spiral pattern throughout the exploration stage in order to thoroughly investigate the solution space. Each new position is analyzed, and better solutions are chosen, ensuring effective global exploration while avoiding premature convergence.

Step 6: Exploitation stage

During the exploitation stage, storms form tornado groups, with half focusing on exploration and the other on exploitation. As storm positions converge and step sizes reduce, the search becomes increasingly targeted. The jet stream helps to avoid local optima, while an adjustable convergence factor directs the search to promising regions, boosting solution accuracy.

Step 6: Termination

The weight hyperparameter of generator from BGLR is optimized using STA; it will repeat step 3 until it attains its halting criteria. Then CPB-BGLR-PGEY defectively assesses advanced approach for fertilized coco peat bricks by improving the accuracy and reducing computational time.

5. Result and Discussion

This section discusses the outcomes of proposed CPB-BGLR-PGEY method. It is simulated in Python using NumPy, TensorFlow, Keras and Scikit-learn. All experiments are conducted on Google Colaboratory (Colab) platform with CPU based computation for reproducible evaluation. The proposed approach is examined utilizing performance measures like Accuracy, Precision, Recall, F1-score, Specificity, ROC and

Computational Time. Obtained outcome of the proposed CPB-BGLR-PGEY method is compared with existing methods like Sustainable Herbo-foam concrete with soap nut and coco-peat: properties and thermal modelling SHF-SNCP-TM [11], Influence of potting media composition on quality flower production of petunia (Petunia hybrida) PMC-CP-PP [12] and Micropropagation and genetic homogeneity assessment of Curcuma aeruginosa Roxb MGH-CP-CAR [13] respectively.

5.1 Performance Measures

The performance of proposed technique is examined under mentioned metrics.

5.1.1 Accuracy

Accuracy is the ratio of instances appropriately anticipated for all instances. This is determined by equation (12).

$$Accuracy = \frac{TP + TN}{FN + TP + FP + TN} \tag{12}$$

Here, TP signifies True Positive; TN denotes True Negative; FP signifies False Positive, FN denotes False Negative.

5.1.2 Precision

This is the ratio of positive occurrences predicted by the model that really occur. It is measured by equation (13).

$$PPV = \frac{TP}{TP + FP} \tag{13}$$

5.1.3 Recall

Recall also known as sensitivity or true positive rate is the ratio of true positives successfully detected by the model and recall. This is determined using equation (14).

$$TPR = \frac{TP}{TP + FP} \tag{14}$$

5.1.4 F1-score

This metric represents a balance of precision and recall with 1 indicating perfect accuracy and recall. This is calculated using equation (15).

$$F1 - Score = \frac{2 \times PPV \times TPR}{PPV + TPR} \tag{15}$$

5.2 Performance Analysis

Figure 2-8 portrays simulation results of CPB-BGLR-PGEY method. The proposed CPB-BGLR-PGEY is compared with existing SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR models

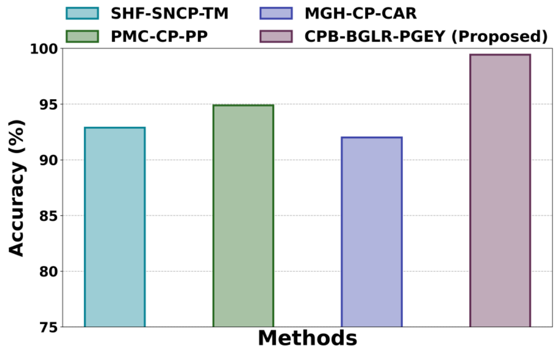

Figure 2: Performance Analysis of Accuracy

Figure 2 compares the accuracy of various approaches for plant growth classification with coco peat-based culture data. The proposed CPB-BGLR-PGEY model has the best accuracy at 99.43%, outperforming SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR. This higher performance is accomplished through the combination of BGLR and STA based hyperparameter optimization, which improves model learning, feature representation, and classification stability. The comparison approaches have a lesser accuracy due to restricted optimization and adaptability to complex plant growth patterns. The proposed model outperforms other techniques with maximum accuracy, showing its effectiveness and resilience.

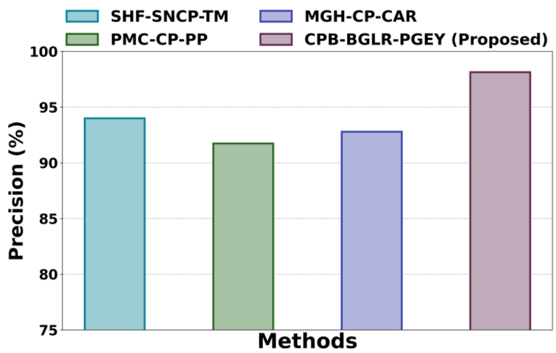

Figure 3: Performance analysis of Precision

Figure 3 compares the precision of various approaches for plant growth classification using coco peat-based cultivation data. The proposed CPB-BGLR-PGEY model has the highest precision 98.14%, surpassing SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR. This increase is due to the combination of BGLR and STA based hyperparameter tweaking, which improves feature discrimination and minimizes false positive predictions in plant health classification. The previous approaches have a lower precision due to limited optimization and adaptation to complicated plant growth fluctuations. The proposed model attains the highest precision, indicating its superiority, reliability and effectiveness.

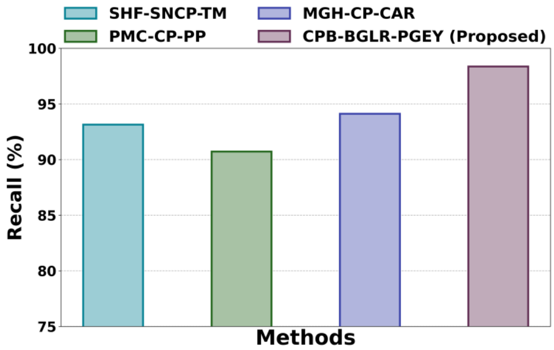

Figure 4: Performance analysis of Recall

Figure 4 shows a recall performance comparison of various approaches for plant growth classification using coco peat-based cultivation data. The proposed CPB-BGLR-PGEY model has the highest recall value at 98.37% outperforming SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR. This large gain is due to the combination of BGLR and STA based hyperparameter optimization, which improves the model's capacity to correctly identify all relevant plant health situations while decreasing false negatives. The comparable approaches have a lower recall due to restricted feature adaptation and inferior parameter adjustment. The proposed model has the highest recall, demonstrating improved sensitivity and reliability in identifying plant health issues when compared to existing techniques.

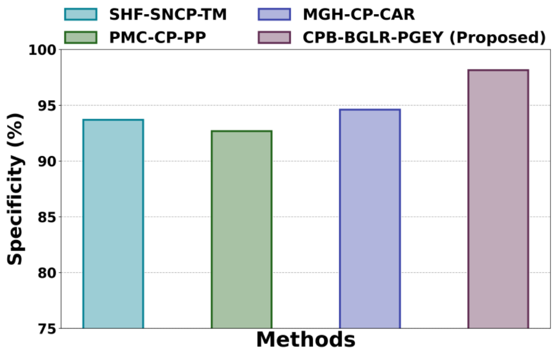

Figure 5: Performance analysis of Specificity

Figure 5 compares the specificity of various approaches for plant growth classification with coco peat-based culture data. The proposed CPB-BGLR-PGEY model has the highest specificity at 98.15%, exceeding SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR. This increase is due to the combination of BGLR and STA based hyperparameter tweaking, which improves the model's capacity to correctly detect negative situations while reducing false positive predictions in plant health categorization. The comparison approaches have poorer specificity due to limited optimization and reduced capacity to distinguish between good and ill plant environments. The proposed model has the highest specificity, displaying greater true negative detection and overall classification reliability when compared to other approaches.

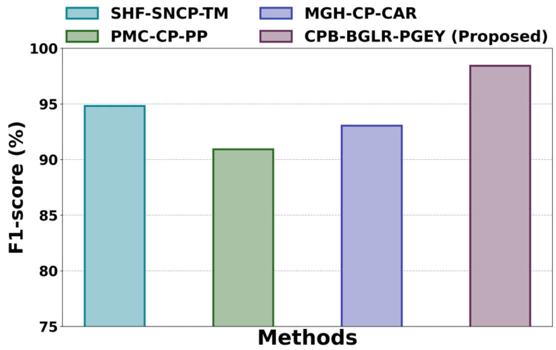

Figure 6: Performance analysis of F1-score

Figure 6 depicts the F1-score comparison of various approaches for plant growth classification based on coco peat cultivation data. The proposed CPB-BGLR-PGEY model has the higher F1-score of 98.44%, beating out SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR. This enhanced performance is attributed to the combination of BGLR and STA based hyperparameter tuning, which ensures a better balance of precision and recall while increasing overall classification robustness. The comparable techniques produce lower F1-scores due to decreased optimization effectiveness and poor flexibility to complicated plant growth changes. The proposed model has the highest F1-score, indicating greater overall performance and balanced predictive potential when compared to existing techniques.

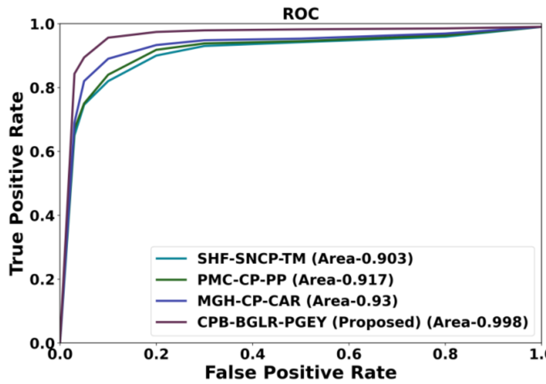

Figure 7: Performance analysis of ROC

Figure 7 depicts the ROC comparison of various approaches for plant growth classification using coco peat-based culture data. The proposed CPB-BGLR-PGEY model has the highest ROC value (0.998), considerably surpassing SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR. This higher result demonstrates that the proposed model discriminate between healthy and harmful plant environments with near-perfect classification capacity. The improvement is due to the combination of BGLR and STA based hyperparameter tuning, which improves feature learning and decision boundary optimization. The comparison approaches have lower ROC values due to poor discriminative capability and suboptimal parameter optimization.

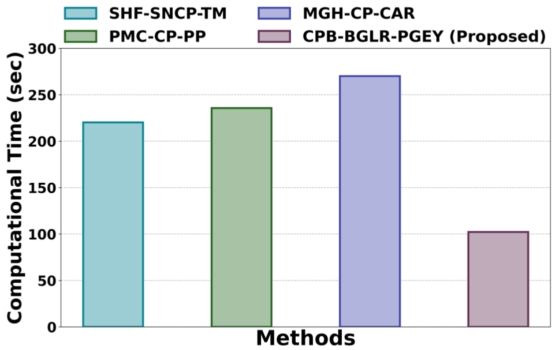

Figure 8: Performance analysis of Computational Time

Figure 8 compares the computing time of various approaches for plant growth classification with coco peat-based cultivation data. The proposed CPB-BGLR-PGEY model has the shortest computational time of 102.4 seconds, greatly surpassing SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR. This reduction in processing time is due to the effective integration of BGLR and STA based hyperparameter optimization, which speeds up convergence and lowers unnecessary computational overhead. The comparative approaches take longer to execute due to less efficient optimization strategies and increasing model complexity. The proposed model has the highest computational efficiency, resulting in shorter processing times and more scalability for real-time coco peat-based agricultural monitoring systems.

Table 2: Comparison of Organic Coco Peat and Normal Coco Peat

Feature	Organic Coco Peat	Normal Coco Peat
Definition	Naturally processed, chemical-free, eco-friendly coco peat	Regular coco peat may be untreated or minimally processed
Processing	Washed, buffered, low EC sometimes enriched	Often unwashed or less processed
Nutrient Content	May contain beneficial microbes & nutrients	Very low nutrients
Salinity	Low	High salt content
Water Retention	High	High water retention may contain excess salts
Aeration	Excellent root aeration	Good but depends on quality
Plant Safety	Safe for seedlings & sensitive plants	Risky for seedlings if not treated
Use Case	Organic farming, hydroponics, nursery plants	General gardening, mixing with soil
Cost	Slightly higher	Cheaper

Table 2 summarizes Organic coco peat is a high-quality, processed growing medium that is low in salt and has adequate aeration better suited for seedlings. In comparison, typical coco peat is less processed have more salt and has a lower nutrient content making it more suitable for general gardening after adequate treatment but at a lesser cost.

6. Conclusion

In this section, the CPB-BGLR-PGEY is successfully implemented to promote sustainable agriculture by combining organic fertilized coco peat bricks with advanced data-driven modeling. This study aims to promote plant growth, soil health and crop output by lowering reliance on chemical fertilizers and encouraging environmentally friendly cultivation practices. Coco peat bricks are good for water retention, aeration and nutrient support. The BGLR model improved with STA ensures accurate plant health categorization and growth prediction. When compared to existing approaches like SHF-SNCP-TM, PMC-CP-PP and MGH-CP-CAR, the system outperforms them with 99.43% accuracy and 98.14% precision. It provides effective monitoring of plant metrics, improved decision-making and optimal resource management all of which contribute to intelligent and sustainable farming. The proposed method has some limitations including dependency on images data quality, computing requirements for optimization and challenges with large-scale real-time implementation. Data unpredictability, environmental conditions and IoT-based field system integration have an impact on performance. Future work will concentrate on integrating IoT sensors for real-time monitoring, increasing model scalability and improving interpretability. Furthermore, using new technologies like AIpowered automation and secure data management solutions can improve reliability and adoption. Overall, the CPB-BGLR-PGEY framework is a cost-effective, scalable and ecologically friendly solution for modern agriculture that promotes long-term productivity and ecological sustainability.

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