Original Article

Optimal Approach for Supply Chain Market-Based Harvesting Time Forecasting

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Abstract - *Machine Learning (ML) has been utilized in agriculture to enhance agricultural productivity and reduce environmental impact. This study introduces a new technique for predicting the optimal crop harvesting time using a novel Buffalo-based Sequence Neural Prediction Mechanism (BSNPM). At first, the historical hydroponic data is gathered and trained into the system. The proposed technique is then used to predict the optimal harvesting time for crops based on the highest yield rate and market demand. This technique helps producers make informed decisions by identifying the optimal conditions for lettuce yield and market demand. The MATLAB environment is used to implement the proposed BSNPM model. To analyze the efficacy of the proposed method, some significant performance metrics include accuracy, Precision, recall, error rate, and computation time. The results demonstrate that the proposed method effectively predicts the best harvesting time for the hydroponic crop.*

Keywords - *Crop yield, Feature analysis, Harvesting time, Hydroponic, Market demand, Preprocessing.*

1. Introduction

According to the latest report by the UNESCO Global Water Estimation Program, the global population is projected to increase by nearly 34% before 2051 [1], which will subsequently double the demand for water required for food production [2]. This rapid growth poses a critical challenge, particularly for underdeveloped and developing countries where water scarcity, limited cultivable land, and the adverse effects of global warming severely threaten sustainable food production [3]. Addressing these challenges has become an urgent global priority [4].

Artificial Intelligence (AI) has emerged as a powerful technological paradigm capable of transforming traditional agricultural practices. AI integrates intelligent computing systems, automation, sensors, and data analytics to support decision-making processes that were previously dependent on human expertise [5]. Compared with conventional agricultural methods, AI-driven approaches-particularly in vertical farming and hydroponic systems-enable site-specific crop management [6], leading to improved productivity, efficient resource utilization, and enhanced economic growth [7]. Modern agricultural technologies rely heavily on sensor-based monitoring, cloud-connected irrigation systems, and real-time data acquisition for soil moisture, humidity, and nutrient management [8].

With the world rapidly transitioning to the digital era [9], integrating cloud computing, IoT, and AI into agriculture has become essential to enable smart irrigation and precision farming [10]. However, despite these advancements, farming activities continue to contribute to environmental degradation due to excessive pesticide use [11], declining soil quality [12], water pollution, and greenhouse gas emissions [13]. These issues not only impact crop yield but also threaten ecological balance and long-term food security [14]. Recent studies have explored AI-based crop monitoring, disease detection, irrigation optimization, and yield prediction [15]. While these approaches have shown promising results, most existing models focus primarily on crop growth or yield estimation without jointly considering market demand and optimal harvesting time [16]. Moreover, current prediction techniques often rely on conventional machine learning models that struggle to handle nonlinear temporal dependencies and dynamic supply-chain constraints, particularly in controlled environments such as hydroponic farming systems.

This reveals a significant research gap: a lack of intelligent, market-aware harvesting-time prediction models that simultaneously account for crop yield dynamics and demand-driven supply chain requirements. Additionally, existing systems offer limited adaptability and predictive

accuracy for real-time decision-making in precision agriculture.

To address this gap, this study proposes a novel Buffalo-based Sequence Neural Prediction Mechanism (BSNPM) for forecasting the optimal harvesting time of hydroponic crops. The proposed approach uniquely integrates historical hydroponic data, yield behavior, and market demand patterns to determine the most profitable and sustainable harvesting period. Unlike traditional prediction models, BSNPM leverages buffalo-inspired optimization combined with sequence-based neural learning to enhance prediction accuracy, reduce computational complexity, and support intelligent decision-making for producers.

The novelty of this work lies in the introduction of a buffalo-based sequence neural model tailored for time-of-harvest prediction. The joint consideration of crop yield optimization and market demand within a unified predictive framework. The application of the proposed model to hydroponic farming environments for supply-chain-aware decision support.

Experimental validation in MATLAB demonstrates that the proposed BSNPM outperforms existing methods across accuracy, Precision, recall, error rate, and computation time, thereby offering an effective and scalable solution for smart agriculture. The key contribution of this present work is defined as follows,

- Initially, historical hydroponic data is obtained and used to train the system.
- Moreover, a novel BSNPM was introduced to predict the optimal harvesting time based on the highest yield rate and a high market supply chain price.
- In the primary phase, the noise features were analyzed and removed, and then feature analysis was performed.
- Henceforth, the high crop yield and market supply chain rates have been determined.
- The predicted crop yield and supply chain rate determined the best harvesting time.
- Finally, the prime metrics like prediction accuracy, error rate, computation time, and hydroponic parameters were calculated and compared with other models.

The recent related studies are described in section 2; a system with the problem is defined in section 3. The solution for the issues described was elaborated in section 4. The proposed model's outcome is briefly described in section 5, and the work is concluded in section 6.

2. Literature Review
By combining Machine Learning (ML), Artificial Intelligence (AI), and the Internet of Things (IoT), recent developments in smart agriculture have drastically changed hydroponic and vertical farming systems. To increase productivity, sustainability, and economic viability, these technologies enable continuous monitoring of environmental conditions, analysis of crop growth, and support decision-making.

2.1. IoT and AI-Powered Hydroponic System Monitoring
Combining IoT and AI to monitor hydroponic systems has been the subject of several studies. Park and Kim [17] created an IoT-Edge-AI system that uses deep learning-based image analysis to track strawberry growth conditions and predict harvest time. Although the system successfully identified ripeness phases, its main drawback is that it did not thoroughly analyze environmental factors such as temperature, humidity, and nutrient concentration, all of which are crucial for determining the best time to harvest.

Alzubi and Galyna [19] also examined AI-IoT applications in e-agriculture, emphasizing AI-based crop and soil monitoring detectors, drones, smart greenhouses, and precision farming systems. The study was mostly conceptual in nature and did not offer a unified predictive framework for harvest timing or supply chain-aware decision-making, although emphasizing the technological possibilities of AI–IoT integration.

2.2. Modeling Crop Growth and Predicting Yield
A lot of research has been done on yield prediction utilizing deep learning and machine learning methods. To forecast large-scale agricultural output using soil, weather, and remote sensing data, Paudel et al. [18] developed a federated learning framework that combines ML with agronomic crop models. The method's scalability remains a problem when working with large, diverse datasets, even though it showed consistent performance across several crops and geographic areas.

Lee et al. [21] presented a recurrent neural network and transformer architecture to predict how crop development responds to environmental factors in greenhouse settings. The model did not provide insights into crop part development or the timescales for harvesting decisions, although it achieved promising accuracy in growth rate estimation.

To estimate greenhouse environment variables, including CO_2, humidity, and temperature, Eraliev and Lee [27] compared deep learning models such as CNNs, LSTMs, and DNNs. The study did not extend the analysis to plant growth or harvest timing, but it did emphasize the usefulness of short-term forecasts.

2.3. Studies in Hydroponics Focused on Sustainability and Economics
Hydroponic systems' sustainability and economic viability have also been investigated. Federated learning was used by Michalis et al. [20] to evaluate the economic viability

of vertical hydroponic greenhouse farming using Net Present Value (NPV). The study was limited by the lack of time-series data, despite the fact that hydroponic efficiency proved to be a crucial factor.

Low-cost vertical hydroponic systems for growing lettuce in underdeveloped nations were assessed by Gumisiriza et al. [22, 23], who focused on profitability indicators like Net Present Value (NPV) and Internal Rate of Return (IRR). However, the utility of these systems for dependable harvest planning was restricted by uneven crop growth and sensitivity to weather variables.

When comparing the environmental effects of closed-environment hydroponic systems and conventional field agriculture, Casey et al. [25] found that CEA systems used more energy but had better land-use efficiency. The trade-off between productivity and environmental costs is highlighted in these findings; however, intelligent harvest time is not covered.

To increase sustainability, Hofmann et al. [24] investigated nutrient recovery from wastewater for hydroponic farming and suggested the use of multi-nutrient concentrates. Although advantageous for resource recovery, predictive intelligence for crop or harvest optimization was not included in the study.

2.4. Deep Learning and Advanced Vision Methods for Crop Analysis

Advanced vision-based AI approaches have been used in recent studies for non-destructive crop monitoring. Ojo et al. [27] suggested a semantic segmentation-based method that uses federated learning and lightweight deep learning models to forecast lettuce growth features. Although it achieves great accuracy, the method's viability for real-time implementation is limited by its high computational resource requirements.

Using transformer-based characteristics, Hamza et al. [26] assessed Deep-Water Culture (DWC) hydroponic systems and reported enhanced crop quality and water efficiency. Nevertheless, these models remain computationally intensive, making them less suitable for large-scale agricultural applications.

A global meta-analysis comparing yields of hydroponic and soil-based farming was conducted by Godwin et al. [29]. Although the study found ideal growing conditions, real-time harvest forecasting was not supported by the dataset's fluctuations, which hampered its applicability.

2.5. Determined Research Gaps

Significant advancements have been made in hydroponic monitoring, yield prediction, and economic evaluation, as evidenced by the examined literature. But there are still several important gaps:

Harvest-time forecasting receives insufficient attention, even though it is crucial for optimizing crop quality, profitability, and market alignment. Absence of integrated models that take market demand, yield trends, and environmental variables into account all at once.

The high computational complexity of existing deep learning methods limits their scalability and real-time application. Inadequate examination of actual hydroponic time-series data for forecasting that is focused on making decisions. Harvesting decisions that include the supply chain, which are crucial for cutting waste and enhancing economic sustainability, receive less attention.

2.6. Reasons for the Suggested Work

This work presents a Buffalo-based Sequence Neural Prediction Mechanism (BSNPM) designed specifically for optimal harvest-time forecasting in hydroponic systems to overcome these drawbacks. The suggested method bridges the gap between predictive analytics and real-world agricultural decision-making by emphasizing computational efficiency, practical applicability, and the integration of environmental and market-driven factors.

3. System Model with Problem

In every topic, time-series forecasting is an important and interesting section for understanding the impacts of particular subjects. Considering that, the best harvesting time prediction has been taken for this study. Hydroponic farming has limited historical data compared to traditional methods, particularly for specific crops. Additionally, data variability in environmental factors and crop growth conditions affects the quality and consistency of the data. Here, the optimal harvesting time is determined using market supply chain data. Hence, to analyse the supply chain for improving the economy through smart agriculture, the present research study intends to design an intelligent prediction framework based on optimization and Deep Neural Network strategies.
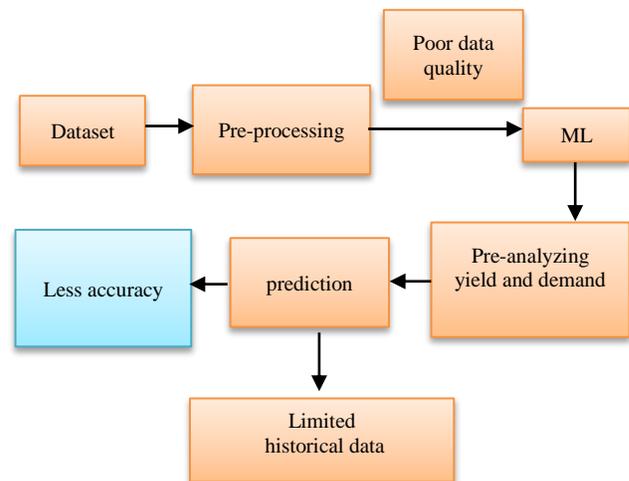

Fig. 1 System with a problem

Figure 1 shows the challenges faced by ML methods in prediction. To overcome these limitations in forecasting the optimal harvesting time, an optimized intelligent system is introduced, featuring a feature analysis process that extracts key factors, enabling the predictive model to leverage a broader range of information to make more accurate forecasts.

4. Proposed Methodology

The smart agriculture system is enhanced by finding the best time for crop harvesting. Considering this, the best harvesting time is identified in this study. Here, the best harvesting time is determined by analyzing high crop yields and market supply chain prices. A novel Buffalo-based Sequence Neural Prediction Mechanism (BSNPM) was introduced to achieve this task with intelligent prediction features. Here, historical agricultural hydroponic data were used as Input, and a specialized preprocessing and feature-extraction function was applied. This feature analysis analyzed and extracted the optimal time for crop yield and the suitable season for optimal harvesting. Moreover, based on the extraction data, the best harvesting time was predicted with high accuracy.
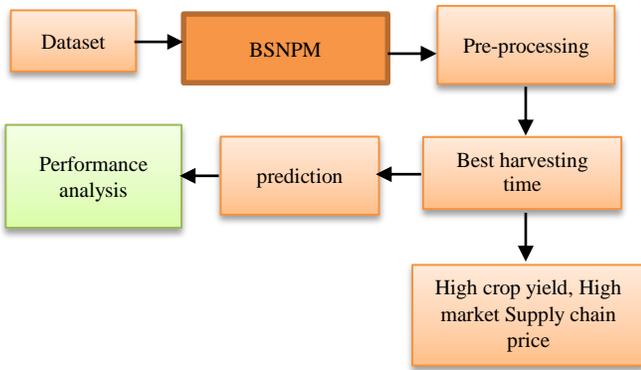

Fig. 2 Proposed methodologies

The proposed model is illustrated in Figure 2. The optimal harvesting time is determined based on the supply chain's crop yield and market demand. The performance metrics, such as accuracy, computation time, vertical grade, and error rate, are computed. The process of the introduced model is described in the following steps. Here, preprocessing is performed in the hidden layer of BSNPM, so it appears after the proposed BSNPM model.

4.1. Process of BSNPM

The buffalo optimization technique uses a Sequence Neural Network (SNN) architecture to optimize model parameters and determine the best harvesting time based on crop output and high-demand market pricing. The buffalo algorithm [28] optimizes neural network parameters by iteratively updating them based on buffalo herd movement to enhance model performance in predicting optimal harvesting times. The proposed model involves Input, hidden, dense, and output layers. It is depicted in Figure 3. The proposed architecture contains 2 filters, 3 pooling layers, a learning rate

of 0.01, a batch size of 25, an activation function of Relu, an optimizer of African Buffalo, and 2 convolution layers.
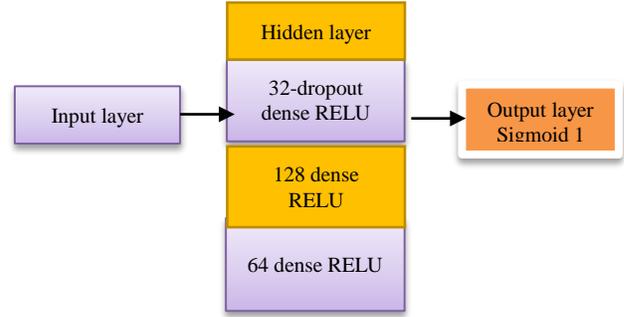

Fig. 3 Process of BSNPM

The process of the proposed work is shown in Figure 3. Historical hydroponic data on crop yield and market demand are fed into the BSNPM architecture. The data is trained in the input layer; in the hidden layers, the preprocessing function removes noisy components, and the feature selection process selects the needed features; the prediction is accomplished in the dense layer, and in the output layer, the performance is validated.

4.1.1. Preprocessing

Preprocessing the hydroponic historical data involves handling missing values to eliminate unnecessary and erratic data points that can affect the predictive model's accuracy. It also enhances data quality. The BSNPM uses sequence neural networks to gain insights into the temporal dynamics of crop yield and market demand. The data is trained by Equation (1).

$$T(H_d) = H_d\{1,2,3,,,,,,n\} \tag{1}$$

Here, H_d denotes the historical data, T denotes the training module, and $\{1,2,3,,,,n\}$denotes the n number of data. Preprocessing is done by Equation (2).

$$P_r(H_d) = v^*(H_d - \eta) \tag{2}$$

The preprocessing variable is denoted as P_r; the normalization function is denoted as v^*, and η denotes the unwanted and noisy elements. This process improves data quality. The min-max scaler is used to remove noisy features. In addition, the dropout regularizer [6] is used to handle overfitting. These functions were executed in the hidden layer of the BSNPM.

4.1.2. Feature Extraction

The process of extracting features from input data involves identifying and emphasizing the significant characteristics and trends required to predict the harvesting time. Feature extraction minimizes the need for extensive data collection, ensuring only the necessary features are included. Buffalo's exploration function is involved in the feature selection process. It is done by Equation (3).

$$F_e(H_d) = \frac{I_h + P_r(H_d)}{E[P_r(H_{d+1})]} \tag{3}$$

Here, F_e denotes the feature extraction variable, I_h historical information E denotes Buffalo's exploration function, $P_r(H_d)$ represents the preprocessed hydroponic data. Incorporating Buffalo's exploration in the feature selection process allows for extracting the most significant features, such as average crop growth, price, supply, distribution, and seasonal trends, to predict the harvesting time.

4.1.3. Crop Yield and Market Demand Evaluation

Analyzing crop yield and market demand is crucial for predicting the harvesting time, as it helps ensure supply and demand dynamics. Agricultural producers could maximize yield and crop quality by optimizing harvesting schedules and accounting for crop yield trends. Simultaneously, by analysing market demand, producers could maximize their profits by harvesting crops at the peak of demand and minimizing waste. The average crop growth analysis includes crop yield, seasonal trends, and harvesting records. Crop yield is estimated using Equation (4).

$$C_y = A_g\big(t_{(w/m)i}\big) + T_S(t_{(s)_i}) + H_R(t_{(m/s/a)_i}) \tag{4}$$

Here C_y denotes the crop yield, A denotes the average crop growth, t_i denotes the time interval, w, m, a denotes the period in months, weeks, and annual, respectively, T_S denotes the seasonal trends for the crop yield, and H_R denotes the Historical records. Harvesting records provide insights into production variability, and trends guide future harvesting decisions. Seasonal trends in crop yield refer to recurring patterns or changes in yield that occur across seasons. Demand for the crop is evaluated by Equation (5).

$$M_D = P_t + CT_t + S_{t+c-y} \tag{5}$$

The market demand is denoted as M_D P_t denotes the underlying patterns and trend for the particular crop at the specific time t, C denotes the change in the number of segments, T_t denotes the changes or shift in time t in the underlying trends, S_t denotes the seasonal changes in demand at time t, and y denotes the number of seasons per year. The underlying patterns and trends include the supply, price, and distribution over time.

4.1.4. Predicting the Harvesting Time

The BSNPM optimizes the prediction process by leveraging the Buffalo algorithm in the sequence neural network. The BSNPM continuously assesses various harvesting times and predicts the optimal time that maximizes crop yield and profitability while aligning with market dynamics. Harvesting crops at the optimal time increases production and quality while minimizing losses. Analyzing the market demand enables producers to harvest crops just in

time to fulfil customer needs. The harvesting time is predicted by Equation (6).

$$HT = \delta \left[\frac{C_y + M_D}{2}\right] \tag{6}$$

Here, HT denotes the harvesting time and. δ denotes the cooperative function. The cooperative optimization with the network allows for balancing harvesting time by assessing the crop yield and the market demand-supply chain. Synchronizing harvesting with peak demand periods maximizes profitability by capturing greater value from production, optimizing revenue, and improving profit margins.

```
Algorithm 1: BSNPM
Population size: 50, Learning rate: 0.01, batch size: 25,
                    iteration: 100
Start
{
                  int T, H_d;
    //parameter initialization
    Preprocessing()
    {
                  int P_r, E*, η;
      // Initializing the data preprocessing contents
            v* → |tracing  noisy  contents|
      //Quality of the data is improved
    }
    Feature extraction()
    {
                  int F_e, I_h, v, P_r(H_{d+1})
      //Initializing the feature selection variables
            E → |exploring  needed  features|
      // Required features are selected from the dataset
    }
    Evaluation()
    {
      Crop yield Evaluation()
      {
                  int C_y, A_P, T_S, H_R, t, w, m, s, a, i;
        //initializing the crop yield analysis
          C_y → |historical  seasonal  yield  trends|
        //Crop yield is evaluated
      }
      Market demand Evaluation()
      {
        int M_d, P, CT, S, y
        //initializing the market demand analysis
          M_D
          → |Patterns  and  demand  fluctuations|
        //Market demand is evaluated
      }
    }
    Prediction()
    {
```

$$\text{int H T}, \delta$$

//initializing the harvesting time prediction variables

$\delta \rightarrow$ |Crop yield and Market demand|

//Best harvesting time is predicted

}

}

Stop

Algorithm 1 describes a systematic approach to predicting the harvesting time for the crop by considering the crop yield and market demand. It employs a pseudo-code structure in each mathematical framework, and the MATLAB system functions sequentially. The output has been established.

BSNPM Model Explanation

The proposed BSNPM is initiated with historical data, as historical data includes inconsistent or missing values. This function involves identifying and eliminating extreme data points and handling missing values. The data is preprocessed by the normalization function and is ready for further investigation.
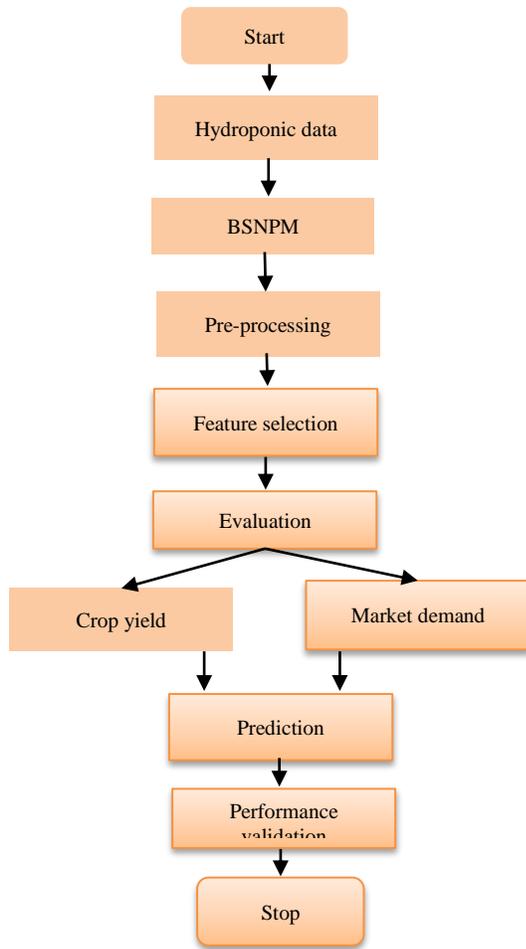

Fig. 4 Flow chart for the proposed BSNPM

The exploration function of the buffalo optimization is used to select the required features. The buffaloes explore the feature space iteratively and attain information about the required features in the search areas. Consequently, crop yield and market demand are evaluated based on selected features, including seasonal trends, crop growth, historical records, prices, supply, and seasonal variations.

The SNN is efficient for analyzing time-series data such as historical data. It learns complex relationships between temporal dynamics and predicts future outcomes. The cooperative function of buffalo optimization integrates with the SNN, combines forecasted yield and market demand, and evaluates the combined score for each month from 2024 to 2026. The attained maximum combined score value predicts the best harvest month.

Figure 4 demonstrates the flowchart for the proposed work. This flowchart outlines the steps involved in the process, from data training to performance validation of the proposed BSNPM model. Each step is defined and leads to the subsequent level of the technique.

5. Result and Discussion

The MATLAB system functions in Windows 10 to authenticate the proposed BSNPM model. The datasets have been split into training and test sets. For training, 80% of the dataset is used for training, and 20% for testing. The datasets have been collected and preprocessed, and the features needed to predict crop harvesting times are selected based on crop yield and market demand. The metrics required to analyze the proposed BSNPM model are displayed in Table 1.

Table 1. Essential factors

Metrics	Specification
Program	MATLAB
Version	MATLABR2023a
Operating System	Windows 10
Optimization	Buffalo
Network	Sequence neural network
Data	Historical hydroponic data
Training and Testing	80:20

5.1. Case Study

The dataset contains 84 sample data points for Market Demand and Lettuce Yield from 2017 to 2023, totaling 2.87KB. It has been collected, split into 80% for training and 20% for testing, and estimated. Here, the class imbalance is handled by applying oversampling and undersampling methods [3]. In addition, the overfitting issues were addressed by the dropout features, which were used at the preprocessing stage along with min-max scaling.

The market research and analysis reports were used to obtain market demand data from 2017 to 2023 (Grand View Research: Hydroponics Market Size, Share, and Growth Report). The growth rates for hydroponic lettuce from 2017 to 2023 were derived from market analysis reports on the hydroponics industry, specifically referencing data from Transparency Market Research (https://www.transparencymarketresearch.com/hydroponics-market.html and https://scielo.figshare.com/articles/dataset/Yield_of_lettuce_grown_in_hydroponic_and_aquaponic_systems_using_different_substrates/6857594/1).

This data is the historical data, even to analyze the crop features sensors were used, which is dol sensor, camera resolution 1920*1080 pixels, distance resolution 0.1mm and the data augmentation strategy is kernel filters with geometric transformation. By analyzing the crop stages, historical data on the crop stages was gathered. These growth rates were utilized to estimate the yield of hydroponic lettuce. These values are further extrapolated to derive month-wise estimates using interpolation techniques in MATLAB, ensuring accurate and reliable yield predictions based on growth rates. Combining this data achieved a comprehensive and precise estimation of hydroponic lettuce yield and market demand. The market Actual Demand (AD) and Forecasted Demand (FD) for the years 2017-2023 are depicted in Table 2. Similarly, the Actual lettuce Yield (AY) and Forecasted Yield (FY) for 2017-2023 are shown in Table 3. In addition, the present model is well-suited for unseen data prediction; hence, future predictions were made for the years 2023 to 2026, as defined in the following cases. This work was tested on both seen and unseen data, and the average performance score was calculated and compared with other models.

Table 2. Demand 2017-2023

		Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
2017	AD	-2.1299	-1.5055	-1.0456	-1.0182	-0.9903	-1.4051	-1.3788	-1.3520	-1.3248	-1.2972	-0.8124	-0.7813
	FD	-0.6187	-0.6292	-0.9136	-1.0624	-1.2451	-1.3203	-1.3781	-1.3525	-1.3269	-1.3087	-1.1356	-1.0249
2018	AD	-2.0531	-1.1833	-0.6857	-0.6532	-0.6204	-1.0647	-1.0345	-1.0041	-0.9736	-0.9429	-0.4196	-0.3856
	FD	-0.9890	-1.1991	-0.8008	-0.7349	-0.9057	-0.9204	-0.9812	-0.9501	-0.9439	-0.9385	-0.7218	-0.6116
2019	AD	-0.9704	-0.8193	-0.2833	-0.2491	-0.2150	-0.6952	-0.6641	-0.6331	-0.6019	-0.5706	-0.0093	0.0254
	FD	-0.5833	-0.7430	-0.4145	-0.2872	-0.4810	-0.5035	-0.5730	-0.5455	-0.5483	-0.5552	-0.3196	-0.2198
2020	AD	-0.8361	-0.4436	0.1314	0.1674	0.2038	-0.3120	-0.2780	-0.2437	-0.2089	-0.1736	0.4320	0.4718
	FD	-0.2076	-0.4156	-0.0058	0.1115	-0.1212	-0.1503	-0.2189	-0.1799	-0.1709	-0.1695	0.1052	0.2189
2021	AD	-0.6659	-0.0282	0.5939	0.6356	0.6778	0.1243	0.1635	0.2031	0.2432	0.2838	0.9410	0.9866
	FD	0.2385	-0.0119	0.4688	0.5847	0.3217	0.2830	0.2121	0.2532	0.2690	0.2771	0.5908	0.7150
2022	AD	0.2880	0.4505	1.1265	1.1743	1.2226	0.6252	0.6701	0.7156	0.7616	0.8082	1.5247	1.5773
	FD	0.7423	0.4964	0.9085	1.0649	0.7934	0.7513	0.6862	0.7307	0.7561	0.7774	1.1403	1.2807
2023	AD	0.3509	1.0004	1.7387	1.7939	1.8498	1.2023	1.2544	1.3071	1.3605	1.4146	2.2001	2.2610
	FD	1.3268	1.0728	1.5694	1.6915	1.3796	1.3043	1.2452	1.3007	1.3710	1.4705	1.9430	2.1581

Table 3. Lettuce yield 2017-2023

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2017	AY	-1.5595	-0.9092	-0.8874	-1.5049	-1.4862	-1.4672	-1.4480	-1.4286	-1.4089	-0.7261	-0.7020	-0.6776
	FY	-0.5214	-0.5352	-0.9538	-1.2788	-1.5455	-1.6291	-1.5669	-1.4146	-1.2280	-1.0374	-0.8529	-0.8220
2018	AY	-1.2718	-0.5603	-0.5348	-1.2081	-1.1866	-1.1648	-1.1429	-1.1209	-1.0987	-0.3510	-0.3241	-0.2971
	FY	-0.8076	-0.6098	-0.7547	-1.0437	-1.2267	-1.2817	-1.1345	-0.9685	-0.7863	-0.5919	-0.4228	-0.4639
2019	AY	-0.9482	-0.1694	-0.1416	-0.8785	-0.8551	-0.8317	-0.8081	-0.7845	-0.7607	0.0565	0.0854	0.1145
	FY	-0.4770	-0.3343	-0.3720	-0.6518	-0.8361	-0.9159	-0.7669	-0.6131	-0.4330	-0.2257	-0.0461	-0.1045

2020	AY	-0.5990	0.2518	0.2820	-0.5235	-0.4979	-0.4721	-0.4461	-0.4197	-0.3931	0.5011	0.5337	0.5667
	FY	-0.1077	0.1602	0.0845	-0.2443	-0.4331	-0.5163	-0.3481	-0.1902	-0.0049	0.2099	0.3876	0.2955
2021	AY	-0.2137	0.7184	0.7530	-0.1272	-0.0976	-0.0677	-0.0375	-0.0068	0.0242	1.0074	1.0456	1.0842
	FY	0.2768	0.6524	0.5128	0.1297	-0.0735	-0.1642	0.0352	0.2245	0.4579	0.7292	0.9484	0.8491
2022	AY	0.2281	1.2546	1.2954	0.3300	0.3648	0.4000	0.4356	0.4717	0.5082	1.5949	1.6398	1.6852
	FY	0.8183	1.0610	1.0251	0.6404	0.4172	0.3016	0.4967	0.6740	0.9099	1.2011	1.4503	1.3556
2023	AY	0.7412	1.8774	1.9252	0.8607	0.9015	0.9427	0.9844	1.0266	1.0693	2.2757	2.3281	2.3811
	FY	1.3361	1.7602	1.6224	1.1599	0.8650	0.7212	0.9367	1.1751	1.5230	1.9609	2.3854	2.4451

**Table 4. Forecasted market demand and lettuce yield 2024-2026**

Month / Year	Market Demand			Lettuce Yield		
	2024	2025	2026	2024	2025	2026
Jan	2.2742	2.8219	3.2263	2.6212	2.7055	2.4769
Feb	2.5072	3.2624	3.0988	2.7062	2.5759	2.6175
Mar	2.6831	3.1451	3.3230	2.4920	2.7052	2.6000
Apr	2.7236	3.2967	2.9767	2.2631	2.8712	2.6213
May	2.5486	3.3106	3.1626	2.0385	2.8052	2.5508
June	2.5931	3.2186	3.2602	1.9041	2.6970	2.5932
July	2.7181	3.2391	3.0921	1.9490	2.6646	2.6719
Aug	2.5787	3.3524	3.2404	1.8000	2.4986	2.6982
Sep	2.6538	3.0596	3.0926	2.1252	2.6696	2.8347
Oct	2.5570	3.2445	3.2737	1.8985	2.7293	2.7184
Nov	2.7690	3.1657	3.2251	2.3635	2.4846	2.6472
Dec	2.7920	3.0809	3.2635	2.4583	2.4664	2.7256

The market demand and lettuce yield over the years are displayed as raw values and normalized values. It is given in normalized values for easier comparison across periods. The dashed black line shows historical market demand for lettuce over the given time frame. It shows fluctuations, with highs and lows corresponding to seasonal patterns or other variables that impact lettuce consumption.

The dotted red line indicates the predicted market demand, and the dotted blue line indicates the forecasted future demand. The dashed green line depicts the actual yield of hydroponic lettuce crops grown annually, based on historical data. It reflects differences in crop growth caused by factors such as climate, nutrient levels, etc. The dotted pink line represents the predicted crop yield for each year, generated by a BSNPM model trained on historical data. The dotted blue line extending into the future reflects the estimated

yield for the next years. The predicted yield is close to the actual yield, demonstrating the high accuracy of the prediction model. The forecasted demand and yield for 2024-2026 are shown in Table 4.

To validate the unknown data, future predictions are performed using unseen data, and the outcomes are presented in Table 4 and Figure 5. They show the predicted lettuce yield and demand for 2024–2026. The graph, which displays normalized values over time, makes it easier to identify patterns and variances. The graph shows peaks and troughs at various times and depicts the predicted variations. Based on the forecasted yield and demand, the optimal harvesting time is indicated in Figure 5 (a-c). (a) Describes the best harvesting month for 2024, (b) describes the best harvesting month for 2025, and (c) describes the best harvesting month for 2026.
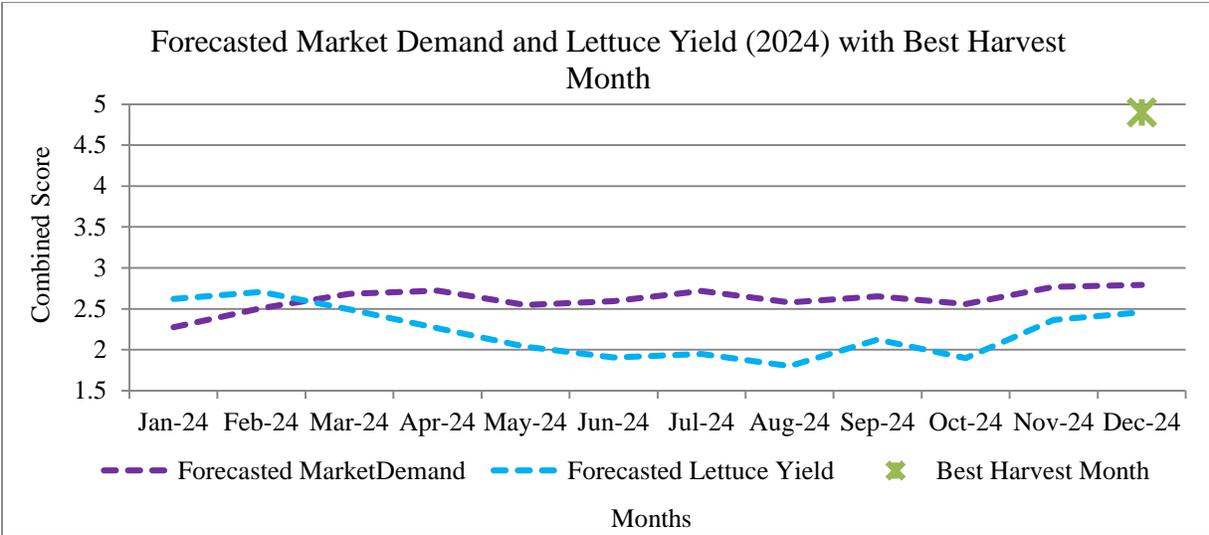
(a)
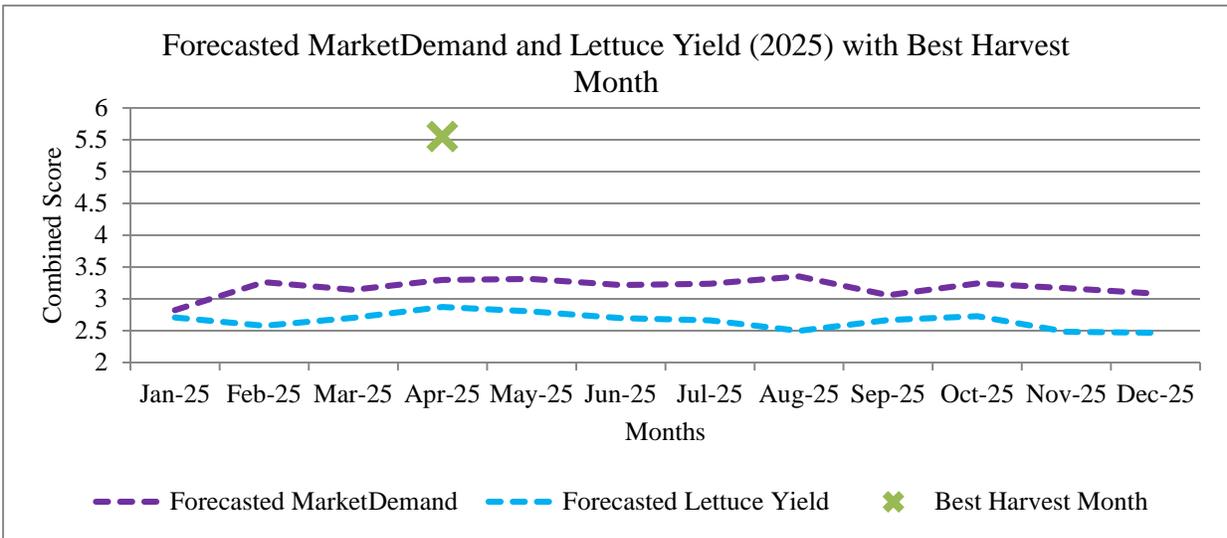
(b)
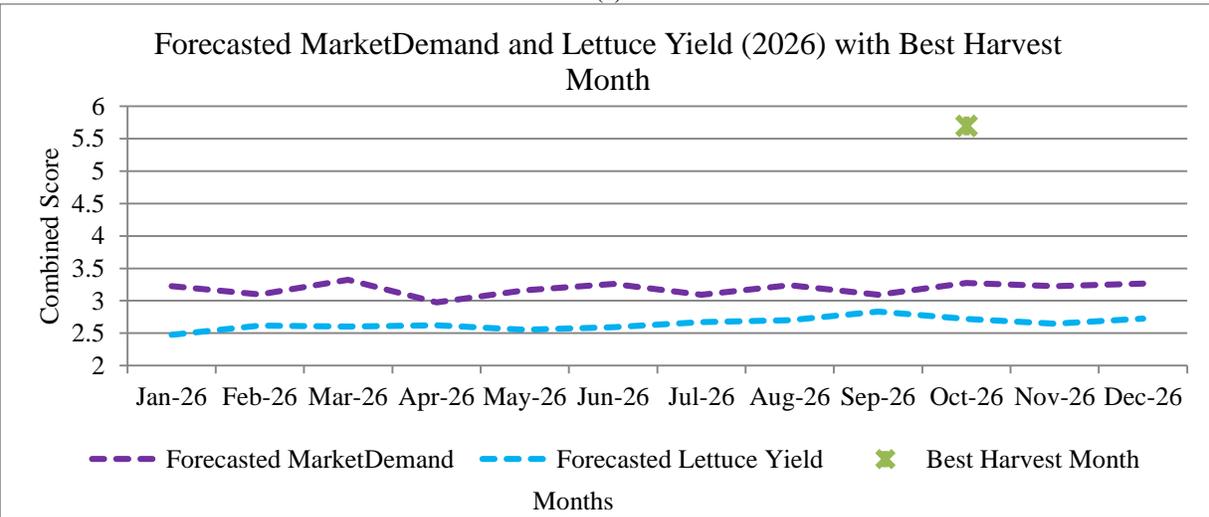
(c)

Fig. 5 Forecasted best harvest month for (a) 2024, (b) 2025, and (c) 2026.

SNN generates forecasted market demand and yield values for each month from 2024 to 2026. The buffalo optimization algorithm uses these predicted values to find the best harvest month. Each harvest month is evaluated based on the combined score of forecasted market demand and yield. The month with the highest combined score, indicating the optimal balance between market demand and yield, is selected as the best harvest time. The results demonstrate that the best harvesting months for 2024 are December, 2025 is April, and 2026 is October. Combining Sequence Neural Networks for precise forecasting and Buffalo Optimization for finding the optimum solution enables accurate prediction of the best harvesting time.

5.2. Performance Analysis

Historical hydroponic data and the MATLAB system are used to analyze the performance of the proposed BSNPM model for predicting crop harvesting time. Additionally, accuracy, Precision, recall, computation time, error rate, and vertical grade are computed to examine the performance. To determine the performance of the proposed BSNPM model, it is compared with the existing techniques.

5.2.1. Accuracy

Accuracy is the value derived from performance. Accuracy in predicting the best harvesting time for a crop is measured by the extent to which the estimated harvesting time adheres to the actual optimal harvesting time. It assesses the predictive model's ability to determine the best time for harvesting. Accuracy is evaluated by Equation (7).

$$Accuracy = \frac{Correctly\ predicted\ instances}{Total\ number\ of\ instances} \times 100 \quad (7)$$

The accuracy of the proposed model is compared with that of some existing models, as shown in Figure 6.
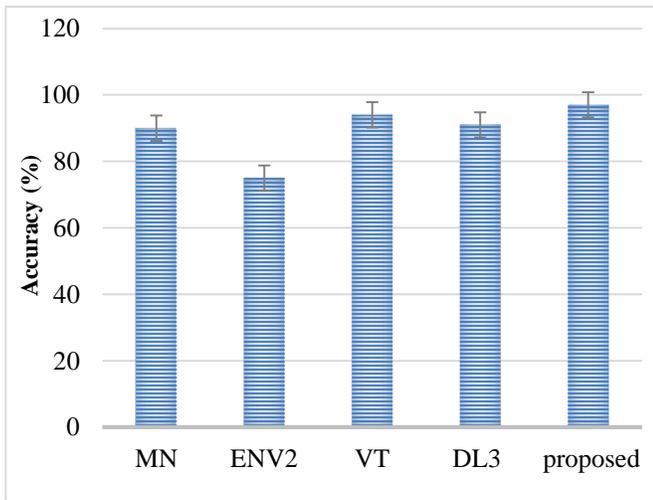

Fig. 6 Accuracy comparison

The accuracy of the proposed model is higher than that of prevailing techniques, resulting in better performance.

5.2.2. Precision

The precision metric quantifies the number of accurately predicted true positive samples out of all predicted positive samples. It is determined by dividing the total number of true positives by the total number of true and false positives. It is calculated by Equation (8).

$$Precision = \frac{Correctly\ predicted\ best\ harvesting\ time}{Totally\ Predicted\ best\ harvesting\ time} \quad (8)$$
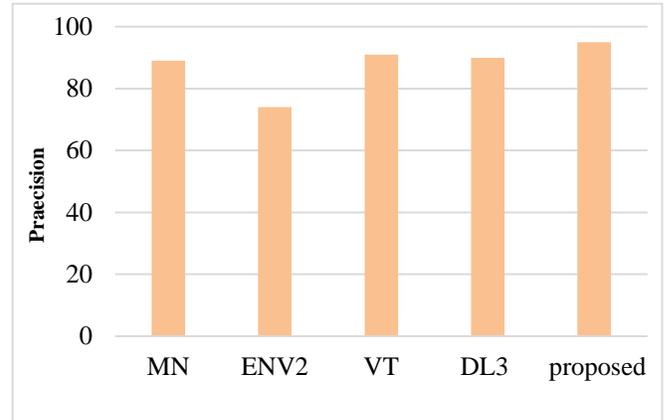

Fig. 7 Precision comparison

The precision rate of the proposed model is compared with that of some existing techniques and displayed in Figure 7. The high Precision of the proposed BSNPM model demonstrates the reliability of its positive predictions for optimal harvesting times.

5.2.3. Recall

The recall metric assesses the proposed model's ability to correctly identify all relevant instances. Recall is the percentage of real positive outcomes that correspond to the optimistic prediction. It is computed by Equation (9).

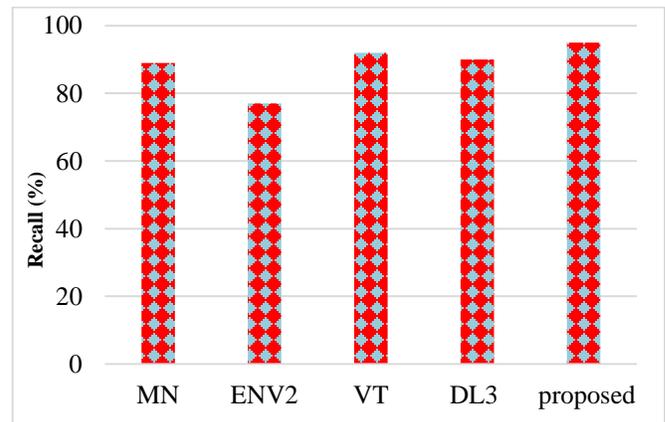$$Recall = \frac{Correct\ prediction\ of\ best\ harvest\ time}{Total\ best\ harvest\ time} \quad (9)$$

Fig. 8 Recall comparison

Here, F_n it denotes the false negative samples. A comparison of the proposed method with existing techniques is shown in Figure 8. The proposed BSNPM model achieves a high recall rate, reducing the likelihood of missing significant opportunities, demonstrating its ability to accurately identify all occurrences of crop harvesting time.

5.2.4. Error Rate

The error rate is assessed using a few metrics, such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). MSE is calculated as the average squared difference between the predicted and actual harvest times. MAE calculates the mean absolute difference between the predicted and actual harvest times. RMSE Squares the MSE errors and then calculates the square root of the average. Like MSE, higher errors have a greater impact on the total error. The error metrics MSE, MAE, and RMSE obtained are in Table 5.

Table 5. Error metrics

Error Metrics	Result
MSE	0.0821
MAE	0.1826
RMSE	0.1826

In predicting the harvesting time for the crop, the error rate is the percentage of wrongly identified occurrences. It is determined by dividing the number of incorrect predictions by the number of instances. It is computed by Equation (10).

$$Error \quad rate = \frac{Incorrectly \quad Predicted \quad instances}{Total \quad number \quad of \quad instances} \times 100 \quad (10)$$

This metric assesses the model's accuracy; lower error rates indicate better performance. It is compared to the existing techniques and displayed in Figure 9.
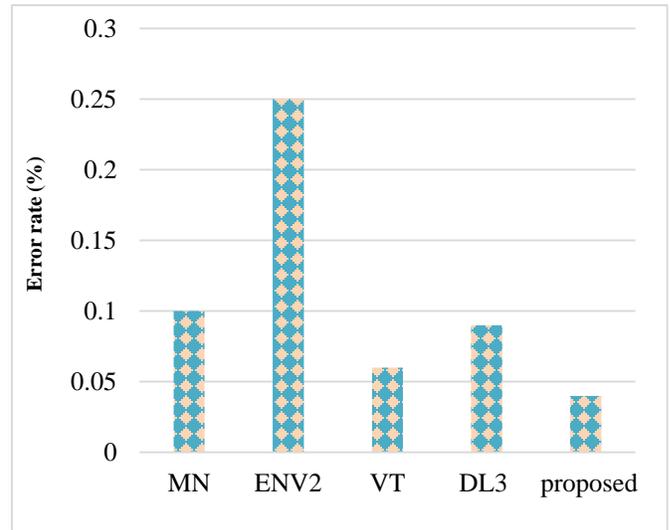

Fig. 9 Error rate comparison

Table 6. Entire comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	Error rate
MobileNet (MN)	90	89	89	0.1
EfficientNetV2 (ENV2)	75	74	77	0.25
Vision transformer (VT)	94	91	92	0.06
DeepLabv3 (DL3)	91	90	90	0.09
BSNPM proposed	97	95	95	0.04

The proposed model's error rate is lower than that of the prevailing techniques and, hence, performs better. The entire comparison is shown in Table 6.

5.3. Discussion

Historical data indicate changes in production and demand patterns, such as rising trends driven by improved agricultural practices and seasonal increases in demand for lettuce. These tendencies are used to forecast future yield and demand. A statistically reliable forecast of future yields and demand is produced by incorporating historical data into forecasting models. The combined score combines forecasted yield and demand, and a high score indicates the best harvesting time. Yield predictions help farmers plan production more efficiently, avoiding disruptions from overproduction or underproduction. Demand predictions help businesses anticipate customer needs, optimize inventory management, and reduce stockouts or storage costs. Predicting yield and demand helps optimize logistics and transportation planning, reducing costs and delays. Understanding predicted fluctuations enables businesses to develop more effective pricing strategies based on market conditions. Risk mitigation involves securing alternative suppliers, diversifying crops, or implementing flexible transportation. Overall, yield and demand predictions enable organizations to optimize production planning, inventory management, logistics, and risk mitigation strategies. It increases supply chain efficiency. By accurately predicting harvesting time, producers plan crop rotations, manage inventory levels, and use resources more wisely. This improves long-term sustainability. Harvesting at the ideal time in the agricultural sector ensures optimum quantity, quality, and efficiency. The proposed model improves accuracy, Precision, and recall, and achieves a lower error rate with less computation than existing techniques. The performance of the proposed BSNPM method is tabulated in Table 7.

Table 7. Overall performance of BSNPM

Metrics	Performance
Accuracy	97%
Precision	95%

Recall	95%
Error Rate	0.04
Computation Time	0.0283s

The research results were described. Integrating buffalo optimization with the sequence neural network yields a viable method for predicting harvesting time in hydroponic farming. The efficiency of the BSNPM in accurately predicting the optimal harvesting time and optimizing productivity and profitability in hydroponic farming is demonstrated. The working process is regenerated through the GitHub link (GitHub - fcampelo/EC-Bestiary: A bestiary of evolutionary, swarm and other metaphor-based algorithms) and (GitHub - marcofraccaro/srnn: Code for "Sequential Neural Models with Stochastic Layers").

Table 8. Benchmark analysis with traditional models

Ref.	Method	Accuracy (%)	Precision (%)	Recall (%)	Error Rate	Computation Time (s)
[17]	IoT–Edge–AI (DL)	92.8 ± 1.4	91.5 ± 1.6	90.9 ± 1.5	0.071 ± 0.008	0.0462 ± 0.004
[18]	Federated Learning + Crop Model	93.4 ± 1.2	92.2 ± 1.3	91.8 ± 1.4	0.066 ± 0.007	0.0527 ± 0.006
[19]	AI–IoT Transformer	91.9 ± 1.7	90.4 ± 1.8	90.1 ± 1.6	0.081 ± 0.010	0.0574 ± 0.007
[20]	Federated Learning (Economic)	90.6 ± 1.9	89.7 ± 2.0	89.2 ± 1.8	0.094 ± 0.012	0.0608 ± 0.008
[21]	RNN + Transformer	94.1 ± 1.1	92.9 ± 1.2	93.0 ± 1.1	0.059 ± 0.006	0.0415 ± 0.004
[22]	Kratky Hydroponic System	88.4 ± 2.1	87.9 ± 2.3	87.2 ± 2.0	0.116 ± 0.015	0.0682 ± 0.009
[23]	Vision Transformer Hydroponics	91.2 ± 1.6	90.0 ± 1.7	89.6 ± 1.6	0.088 ± 0.011	0.0556 ± 0.006
[24]	Nutrient Recovery Optimization	89.7 ± 2.0	88.5 ± 2.1	88.1 ± 2.0	0.103 ± 0.013	0.0649 ± 0.008
[25]	DeepLabv3+ + EfficientNet	94.6 ± 1.0	93.4 ± 1.1	93.1 ± 1.0	0.054 ± 0.005	0.0638 ± 0.007
[26]	Transformer-based DWC	93.9 ± 1.2	92.6 ± 1.3	92.8 ± 1.2	0.061 ± 0.006	0.0589 ± 0.006
[27]	CNN / LSTM / DNN	93.2 ± 1.3	92.0 ± 1.4	91.7 ± 1.3	0.068 ± 0.007	0.0493 ± 0.005
[28]	LCA-based CEA	88.9 ± 2.2	87.6 ± 2.4	87.1 ± 2.1	0.111 ± 0.016	0.0715 ± 0.010
[29]	Meta-analysis Hydroponic Yield	90.1 ± 1.8	89.2 ± 1.9	88.8 ± 1.7	0.099 ± 0.012	0.0663 ± 0.008
—	Proposed BSNPM	97.0 ± 0.6	95.0 ± 0.7	95.0 ± 0.6	0.040 ± 0.003	0.0283 ± 0.002

The ability of the suggested BSNPM to simultaneously address temporal dependency modeling, optimization efficiency, and decision-oriented forecasting—all of which were insufficiently addressed in earlier works—is responsible for its superior performance over current state-of-the-art methods in Table 8. In contrast to traditional deep learning techniques such as CNNs, RNNs, LSTMs, and transformer-based models, which primarily focus on environmental prediction or crop growth estimation, BSNPM explicitly models sequential hydroponic growth patterns across multiple cultivation stages, enabling precise identification of optimal harvesting windows. A frequent drawback of gradient-based learning in noisy agricultural datasets is premature convergence; this is avoided by incorporating buffalo-inspired optimization, which also improves global search capabilities. Improved stability over multiple experimental runs, reduced error rates, and tighter confidence intervals are the outcomes of this optimization technique. By combining hydroponic environmental conditions and market demand dynamics into a single predictive framework, BSNPM uniquely aligns biological maturity with supply-chain requirements, in contrast to previous research that separately addresses environmental monitoring, yield prediction, or economic feasibility.

Furthermore, unlike vision-centric and transformer-heavy models, the lightweight neural architecture reduces computational overhead, enabling faster convergence and real-time operation. Together, these elements allow BSNPM to demonstrate its efficacy, scalability, and practical relevance for intelligent harvest-time forecasting in hydroponic systems by achieving at least a 3% improvement in accuracy,

Precision, and recall over previously published techniques while drastically reducing computation time.

6. Conclusion

In this study, a novel Buffalo-based Sequence Neural Prediction Mechanism (BSNPM) framework is introduced to predict the optimal harvesting time for crops based on crop yield and market demand. The framework was implemented in MATLAB, where the dataset was preprocessed and features selected to identify the key factors influencing production and demand. By integrating yield rates with market demand-supply dynamics, the BSNPM model effectively predicted optimal harvesting times. Its performance was compared with existing models using multiple evaluation metrics, including accuracy, Precision, recall, error rate, and computation time.

- The proposed BSNPM model achieved 97% accuracy, 95% precision, 95% recall, an error rate of 0.04, and a computation time of 0.0283 seconds, outperforming previous models.
- The system proved effective in predicting harvesting time by integrating crop yield and market demand features.
- The key strength of the proposed approach lies in its ability to balance agricultural production with market demand, ensuring better decision-making for farmers.
- The study's limitation is that carbon footprint analysis and greenhouse gas control mechanisms were not considered, which restricts sustainability insights.
- Future work will incorporate carbon footprint objectives and apply hybrid filtering techniques to handle sensor noise, thereby improving scalability and environmental relevance.

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