International Journal of Electrical and Computer Engineering (IJECE)
Vol. 15, No. 1, February 2025, pp. 783~791
ISSN: 2088-8708, DOI: 10.11591/ijece.v15i1.pp783-791

Seasonal auto-regressive integrated moving average with bidirectional long short-term memory for coconut yield prediction

Niranjan Shadaksharappa Jayanna, Raviprakash Madenur Lingaraju
Department of Computer Science and Engineering, Kalpataru Institute of Technology, Tiptur, affiliated to Visvesvaraya Technological University, Belagavi, India

Article Info

Article history:

Received May 27, 2024
Revised Sep 5, 2024
Accepted Oct 1, 2024

Keywords:

Bidirectional long short-term memory
Coconut yield prediction
Label encoder
Seasonal auto-regressive integrated moving average
Whale optimization algorithm

ABSTRACT

Crop yield prediction helps farmers make informed decisions regarding the optimal timing for crop cultivation, taking into account environmental factors to enhance predictive accuracy and maximize yields. The existing methods require a massive amount of data, which is complex to acquire. To overcome this issue, this paper proposed a seasonal auto-regressive integrated moving average-bidirectional long short-term memory (SARIMA-BiLSTM) for coconut yield prediction. The collected dataset is preprocessed through a label encoder and min-max normalization is employed to change non-numeric features into numerical features and enhance model performance. The preprocessed features are selected through an adaptive strategy-based whale optimization algorithm (AS-WOA) to avoid local optima issues. Then, the selected features are given to the SARIMA-BiLSTM to predict the coconut yields. The proposed SARIMA-BiLSTM is adaptable to handling a widespread of various seasonal patterns and captures spatial features. The SARIMA-BiLSTM performance is estimated through the coefficient of determination (R2), mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE). SARIMA-BiLSTM attains 0.84 of R2, 0.056 of MAE, 0.081 of MSE, and 0.907 of RMSE which is better when compared to existing techniques like multilayer stacked ensemble, convolutional neural network and deep neural network (CNN-DNN) and autoregressive moving average (ARIMA).

Corresponding Author:

Niranjan Shadaksharappa Jayanna
Department of Computer Science and Engineering, Kalpataru Institute of Technology, affiliated to Visvesvaraya Technological University
NH-206, Vidya Nagar, Tiptur, Karnataka 572201, India
Email: niranjansj555@gmail.com

1. INTRODUCTION

The coconut is a significant crop which plays a crucial role in economies of numerous countries, including India, the Philippines, and Indonesia [1]. Generally, it is known as the tree of heaven, because all parts of the plants are useful and the main source of income for farmers [2]. Worldwide, it is grown in 93 countries in 12 million hectares areas with a yearly production of 59.98 million nuts. India has secured the third position globally, producing an impressive 10.56 million coconuts annually [3], [4]. Accurately predicting coconut yields is crucial in mitigating potential disasters during different stages of crop growth, impacting yield levels significantly. Monitoring consecutive time series data throughout growth periods is essential for effective coconut yield prediction [5], [6]. The yield is a complex which varies through factors like variety and age. The matured nuts are taken as yield since it contains solid endosperm which is utilized for yield prediction [7], [8]. Temperature is a significant factor in a growth of coconut nuts and huge temperature damages the root growth [9]–[11]. Real-time and deep learning (DL) techniques are employed to enhance the early detection and enhance the coconut yield which offers better yield prediction [12], [13]. Remote sensing plays a prominent role in calculating crop damages and predicting crop yield. By applying these methods, the production of hybrid coconuts and local tall at dual leaf clipping levels is effectively predicted [14]–[16]. Iniyan and Jebakumar [17] developed a mutual information feature selection (MIFS) for crop yield prediction using multilayer stacked ensemble regression (MSER). The developed model intricated the prediction procedure of crop yield on soybean and crop which obtained better performance according to phenotype factors. Several non-linear and linear techniques are employed in the model for predicting crop yield. However, crop data necessitates numerous preprocessing to fitting baseline supplies that are not initiated for yield prediction.

Oikonomidis *et al.* [18] introduced a hybrid convolutional neural network and deep neural network (CNN-DNN) for crop yield prediction. It was effective for prediction due to its outliers with huge variance in different areas which were employed to create yield estimation. The feature selection utilized feature engineering techniques which were employed to obtain efficient performance. The introduced model required a significant capability of data and it cannot consider the time-series data. Peng *et al*. [19] suggested an incorporated technique on BiLSTM-sine cosine algorithm (SCA) for solar radiation prediction. Initially, complete ensemble empirical mode decomposition through adaptive noise (CEEMDAN) was applied for prediction. The auto-correlation function (ACF) and the partial auto-correlation function (PACF) were utilized to identify radiation pattern of decomposed sub-modes. However, the developed model required a vast amount of captured data which is complex to obtain. Prasert and Rungreunganun [20] presented a coconut yield prediction through auto-regressive integrated moving average (ARIMA). Its autonomous variables offered enhanced accuracy without any individual variables by designating appropriate factors to produce the prediction model. However, huge attention was required to fascinate and inspire farmers in coconut production. Novarianto [21] implemented an aerial photography technique through drones for determining data effectiveness by integrating standard sample population in local tall coconut. The population density of every area is established through various factors and palms are expired and the results of pests are not appropriate for coconut production. The existing techniques have limitations such as requiring extensive data processing and unable to handle time-series data. These methods necessitate significant preprocessing to fit baseline models that are not initiated for yield prediction and they struggled to fascinate and motivate farmers in coconut production. Moreover, they are unable to handle a widespread of various seasonal patterns and captures spatial features because of local optima issues. To overcome this issue, this research proposed seasonal auto-regressive integrated moving average-bidirectional long short-term memory seasonal auto-regressive integrated moving average-bidirectional long short-term memory (SARIMA-BiLSTM) for coconut yield prediction which is adoptable to handle various seasonal patterns and spatial features. Additionally, adaptive strategy-based whale optimization algorithm (AS-WOA) is used for feature selection process which avoids local optima issues and enhances the convergence rate. The paper contribution is as:

a. The dataset is preprocessed using label encoding and min-max normalization which ensures non-numeric data is transformed effectively thereby contributing to enhance the model performance. The label encoder is used to convert categorical features into numerical features and min-max normalization is applied to scale the features.
b. The preprocessed features are then selected using AS-WOA, which enhances the convergence rate and effectively mitigates the risk of getting trapped in local optima thereby ensuring optimal feature selection.
c. The selected features are then fed into SARIMA-BiLSTM model which is adaptable and capable of handling a wide range of seasonal patterns and effectively captures spatial features which leads accurate and reliable predictions.

This research paper is prepared as section 2 defines proposed methodology. Section 3 defines the results and discussion. The conclusion of this paper is given in section 4.

2. PROPOSED METHOD

The SARIMA-BiLSTM is proposed in this manuscript for predicting coconut yield in Kerala. The collected dataset is preprocessed through label encoder and min-max normalization which is employed to change non-numeric features into numerical features and enhance model performance. The preprocessed features are selected through AS-WOA which enhances the convergence rate and avoids local optima issues. Then, the selected features are given to the SARIMA-BiLSTM for predicting the coconut yields. Figure 1 presents the block diagram of proposed methodology.

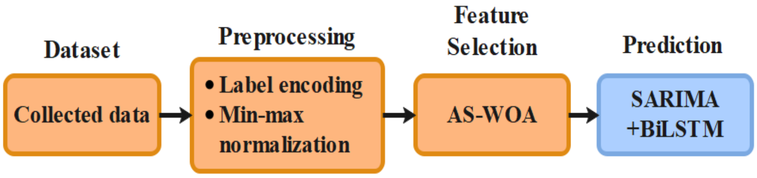

Figure 1. Block diagram of the proposed methodology

2.1. Dataset

The coconut holds a prominent position as a cultivation crop in Kerala, which covers approximately 39% of the region. The dataset sourced from the department of economics and statistics, Kerala, spans from 2011 to 2021 and encompasses yearly coconut yields from 10 districts: Alappuzha, Kozhikode, Idukki, Kottayam, Kollam, Ernakulam, Thrissur, Wayanad, Kasaragod and Palakkad. This dataset comprises around 120 records annually, equating to an approximate production of 8 million nuts.

2.2. Preprocessing

The preprocessing techniques employed in this research are label encoder and min-max normalization. These techniques improved the data quality which is explained in the following sub-sections. Label encoding transforms non-numeric features into numerical ones, facilitating the model's ability to learn from the data. When dealing with datasets, certain features may not be in the appropriate format, necessitating their conversion into numerical values through label encoding. This process reduces data volume by encoding numeric values, resulting in efficient memory usage. The min-max normalization is utilized for changing raw data into a standardized format which enhances the model performance. The maximum score of the features is changed to 1, the minimum score of the features is changed to 0 and other scores of features are changed between 0 and 1 [22]. It is expressed in (1), y' is a normalized score, y is an actual value, $max(y)$ and $min(y)$ is a maximum and minimum score of y.

$$y' = \frac{y - \min(y)}{\max(xy) - \min(y)} \tag{1}$$

2.3. Adaptive strategy-based whale optimization algorithm for feature selection

The whale optimization algorithm (WOA) is employed for feature selection of coconut yield prediction which avoids local optima issues. It is a population-based algorithm inspired by whale’s bubble-net feeding. WOA comprises three stages encircling, exploitation and exploration which denotes the whales' hunting procedure. The encircling prey identifies prey positions and encircles the targets, exploitation denotes spiral attack, and exploration denotes random search prey.

2.3.1. Encircling prey

This phase is used to identify the prey positions and it designates search agents according to different whale distances from prey. After identifying the search agent, every whale updates the positions according to the search agent. The optimum prey positions are unidentified at the initial optimum solution closer to the probable solution is considered through WOA. After estimating the best solutions, search agents try to update their positions to the best search agent for attaining the current best locations that are expressed in (2) to (5),

$$\vec{D} = \beta \cdot \vec{X^*}(t) - \vec{X}(t) \tag{2}$$

$$\vec{X}(t+1) = \vec{X^*}(t) - \alpha \cdot \vec{D} \tag{3}$$

$$\alpha = 2 \cdot m \cdot n - m \tag{4}$$

$$\beta = 2 \cdot n \tag{5}$$

where, $\vec{D}$ denotes present position vector of optimal metrics, t is a present iteration, $\vec{X^*}(t)$ is a present best arrangement location vector at tth iteration. $\vec{X}(t)$ denotes position of search agent, α is ranges among $[-m, m]$, here m reduces linearly from 2 to 0 over the whole exploitation and exploration phases. The m is estimated by $m = 2 - 2 * t/t_{max}$ which stays similar through whole process. The n is random number within $[0, 1]$, t_{max} is a maximum iteration.

2.3.2. Exploitation stage

This phase contains two various mechanisms such as shrinking enriching process and spiral updating position [23] which is explained in bellow: In the shrinking enriching process, search agent position update is classified with search space by best solution of agent. In spiral updating position, candidate new position is evaluated. The goal of the shrinking enriching mechanism is to minimize the evaluated value of m which originates the humpback whale behavior. The search agent position update is categorized within the search space limited through the best solution of the agent which is designated through α random values. The candidate's new positions are evaluated by utilizing spiral updating position mechanism. The shrinking enriching mechanism and spiral updating position are expressed in (6) to (9),

$$\vec{\mathrm{D}} = \overrightarrow{\mathrm{X}^*}(\mathrm{t}) - \vec{\mathrm{X}}(\mathrm{t}) \tag{6}$$

$$\vec{\mathrm{X}}(\mathrm{t}+1) = \vec{\mathrm{D}} \cdot \mathrm{e}^{\mathrm{wl}} \cdot \cos(2\pi \mathrm{l}) + \overrightarrow{\mathrm{X}^*}(\mathrm{t}) \tag{7}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \alpha \cdot \vec{D}, \quad if\ p < 0.5 \tag{8}$$

$$\vec{X}(t+1) = \vec{D} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) \quad if\ p \geq 0.5 \tag{9}$$

here, $\vec{D}$ is highest distance among whale and prey, w denotes constant which explains geometry of logarithmic spiral, and l is produced within the range of $[-1, 1]$ correspondingly. The decision about specific process is designated through a random number of $\mathrm{p} \in [0, 1]$ focuses on uniform distribution. If $\mathrm{p} < 0.5$, the agents continue to the leader according to the shrinking encircling process. If $\mathrm{p} \geq 0.5$, search agent position is modernized based on spiral updating position.

2.3.3. Exploration stage

In this stage, the whales randomly search according to their positions and α is designed as a random value either lesser than 1 or greater than -1. The $\alpha \geq 1$ condition has happened, and exploration is forced on humpback whales to global optimum and remove local minima. The exploration is expressed in (10) and (11), $\vec{\mathrm{D}}$ denotes distance between ith whale and prey, $\overrightarrow{\mathrm{X}_{\mathrm{rand}}}$ denotes random location vector. The arbitrarily sorted whale from presently considered community. The adaptive strategy-based WOA is explained in the following section.

$$\vec{D} = \beta \cdot \overrightarrow{X_{rand}} - \vec{X} \tag{10}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}}(t) - \alpha \cdot \vec{D} \tag{11}$$

2.3.4. Adaptive strategy-based WOA

The population of individual diversity will be reduced when the algorithm is iterated to the further stages. The deduction causes individuals to search space for decay in the position of local optimum. During this time, a small number of whale populations are searched continuously and it outputs premature convergence and easily falls into local optimum. So, an efficient balance of growth and exploration capabilities of the algorithm is to enhance searching abilities. The adaptive inertia weight strategy is introduced into traditional WOA to balance the local and global search capabilities of WOA which enriches population diversity. It enables the algorithm to maintain a specific intensity of the search state in further iteration stages which avoids local optima issues and premature convergence. The inertia update strategy is expressed in (12) and (13), The ω is mathematically expressed in (14) to (16),

$$\vec{X}(t+1) = \begin{cases} \omega \cdot \overrightarrow{X^*}(t) - \alpha \cdot \vec{D}, & if\ p < 0.5 \\ \omega \cdot \vec{D} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) & if\ p \geq 0.5 \end{cases} \tag{12}$$

$$\vec{X}(t+1) = \omega \cdot \overrightarrow{X_{rand}}(t) - \alpha \cdot \vec{D} \tag{13}$$

$$\omega = \frac{C \times \sqrt{t}}{M} \times \left(1 - \frac{t}{T_{max}}\right) \tag{14}$$

$$M = \sqrt{H + N^2} \tag{15}$$

$$H = \frac{\sum_{j=1}^{N}\left(Ub_{i,j} - Lb_{i,j}\right)^2}{t} \quad (16)$$

where, ω is an adaptive inertia weight that is adjusted through the number of iterations. $C = 0.1$, t and T_{max} are present and maximum iterations, N is many dimensions. The $\sqrt{t}$ and H plays a major role in the initial stage of the iteration process. This process enables the individual populations to escape from their present positions and exploration with large searches to enhance the algorithm capabilities to avoid local optima issues.

2.4. Prediction

The coconut yield is predicted through seasonal auto-regressive integrated moving average (SARIMA) with the BiLSTM model which is adaptable to handling a widespread of various seasonal patterns. The BiLSTM processes the data into dual networks such as forward and backward long short-term memory (LTSM) and the result of these networks are integrated at every time. The BiLSTM captures spatial features and bidirectional time dependencies from historical data which improves the model performance.

2.4.1. Seasonal ARIMA

The ARIMA is a time series forecasting technique used for changing stationary from non-stationary time series data through applying variances. It determines current time-series values through previously predicted errors and values. Similarly, the SARIMA employed past values but considered seasonality as a parameter. The improvisation of the ARIMA is a seasonal ARIMA (SARIMA). The SARIMA is expressed in (17).

$$\text{SARIMA} = \text{ARIMA}\ (\text{p}, \text{d}, \text{q})(\text{P}, \text{D}, \text{Q})s \quad (17)$$

Here, p and P denotes autoregressive and seasonal autoregressive order, d and D denotes difference and seasonal difference order, q and Q denotes moving average and seasonal moving average order, s is a seasonal length in a data. The SARIMA captures both seasonal and non-seasonal patterns in data which creates forecasted model. The SARIMA is adaptable to handling a widespread of various seasonal patterns and captures spatial features. The certain modeling procedure of SARIMA is defined:

a. Stationarity test: The augmented dickey-fuller (ADF) and auto-correlation function (ACF) are utilized to find whether the time-series data was stable or not. If it is not stable, then the d and D-order differences are applied.
b. Ljung-Box test: It is accomplished on a sequence, if the p score is lesser than the significance level, the sequence is constant. If the sequence is not constant, the modeling is continued.
c. Model identification and order determination: To fit the SARIMA, the Python grid search is employed.
d. Model selection: The optimum model is selected using the least Akaike information criterion (AIC).
e. Model test: By utilizing the residual white noise test, the model success fitting is determined.
f. Prediction: The constructed model is utilized for prediction.

2.4.2. Bidirectional long short-term memory

The LSTM stores the input data in a hidden layer including the time series concept. Through this, the input data is stacked in a time sequence at the hidden layer, and the new input data is replicated in the result. The BiLSTM is an improved version of conventional LSTM which takes past and upcoming states to enhance the prediction performance. The BiLSTM processes the data into dual networks such as forward and backward LSTM [24] and the result of these networks are integrated at every time. Figure 2 presents the architecture of BiLSTM.

In a forward layer, its evaluation is accomplished from time $[1, \text{t}]$ and its output is attained and saved at every time. In the background layer, the evaluation is reversed over time $[t, 1]$ and its output is attained and saved at every time. Lastly, at every moment, the final result is attained through integrating output for the respective time of the forward and backward layers. The BiLSTM is mathematically expressed in (18) to (20).

$$\overrightarrow{\text{h}}_\text{t} = \tanh\left(\text{W}_{\text{x}\overrightarrow{\text{h}}}\text{x}_\text{t} + \text{W}_{\overleftarrow{\text{h}}\overleftarrow{\text{h}}} + \text{b}_{\overleftarrow{\text{h}}}\right) \quad (18)$$

$$\overleftarrow{h}_t = tan\,h\left(W_{x\overleftarrow{h}}x_t + W_{\overleftarrow{h}\overleftarrow{h}} + b_{\overleftarrow{h}}\right) \quad (19)$$

$$\text{y}_\text{t} = \text{W}_{\overleftarrow{\text{h}}}\overrightarrow{\text{h}}_\text{t} + \text{W}_{\overleftarrow{\text{h}}\text{y}}\overleftarrow{\text{h}} + \text{b}_\text{y} \quad (20)$$

where, $\vec{h}_t$ and $\overleftarrow{h}_t$ are forward and backward hidden layer outputs which are presented through superscripts $(\vec{.})$ and $(\overleftarrow{.})$ correspondingly. The $W_{x\vec{h}}$, $W_{\vec{h}\vec{h}}$ and $W_{\vec{h}y}$ are weight matrices of input, hidden and output layers. The b_y, $b_{\vec{h}}$ and $b_{\overleftarrow{h}}$ are output bias vectors of input, hidden and output layers correspondingly. The BiLSTM captures spatial features and bidirectional time dependencies from historical data which improves the model performance.

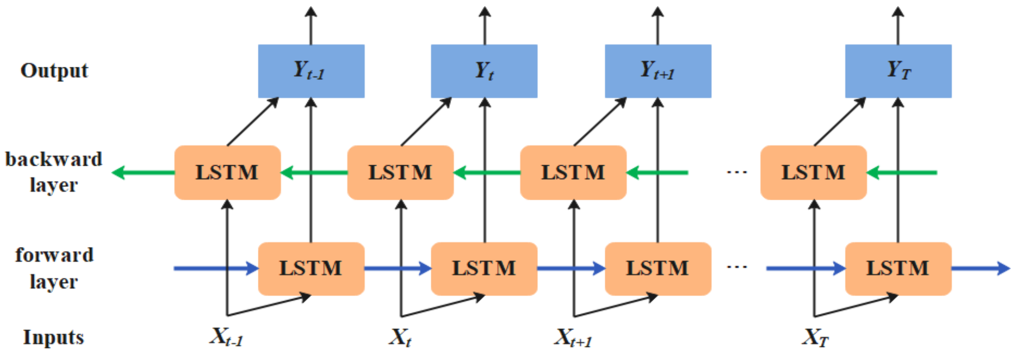

Figure 2. Architecture of BiLSTM

3. RESULTS AND DISCUSSION

The SARIMA-BiLSTM is evaluated through Python 3.10 with RAM 8 GB, intel core i5 and OS windows 10. The proposed SARIMA-BiLSTM is adaptable to handling a widespread of various seasonal patterns and captures spatial features. The proposed SARIMA-BiLSTM is adaptable to handling a widespread of various seasonal patterns and captures spatial features. The metrics like R2, MAE, MSE, and RMSE are employed for evaluating model performance [25].

3.1. Quantitative and qualitative analysis

The quantitative and qualitative analysis of the proposed SARIMA-BiLSTM is assessed with R2, MAE, MSE, and RMSE metrics. The BiLSTM captures spatial features and bidirectional time dependencies from historical data which improves the model performance. The proposed SARIMA-BiLSTM is adaptable to handling a widespread of various seasonal patterns and captures spatial features. Table 1 presents the AS-WOA performance and Table 2 presents the SARIMA-BiLSTM performance.

Table 1. Performance of AS-WOA

Method	R2	MAE	MSE	RMSE
PSO	0.93	0.089	0.098	0.983
GWO	0.90	0.085	0.093	0.957
CSO	0.88	0.078	0.089	0.931
WOA	0.86	0.073	0.084	0.926
AS-WOA	0.84	0.056	0.081	0.907

Table 2. Performance of SARIMA-BiLSTM model

Method	R2	MAE	MSE	RMSE
CNN	0.92	0.092	0.092	0.957
RNN	0.89	0.086	0.089	0.949
LSTM	0.87	0.081	0.086	0.926
BiLSTM	0.85	0.075	0.083	0.915
SARIMA-BiLSTM	0.84	0.056	0.081	0.907

Table 1 presents the performance of AS-WOA through R2, MAE, MSE and RMSE. The performance of particle swarm optimization (PSO), grey wolf optimization (GWO), cat swarm optimization (CSO) and WOA are matched with AS-WOA. The AS-WOA attains better results through R2, MAE, MSE, and RMSE values of about 0.84, 0.056, 0.081, and 0.907 appropriately when compared to existing algorithms. Table 2 presents the performance of SARIMA-BiLSTM through R2, MAE, MSE, and RMSE. The convolutional neural network (CNN), recurrent neural network (RNN), LSTM, and BiLSTM performance are matched with SARIMA-BiLSTM performance. The SARIMA-BiLSTM attains better results through R2, MAE, MSE, and RMSE values of about 0.84, 0.056, 0.081, and 0.907 appropriately when compared to existing algorithms. Figures 3, 4, and 5 present the epoch v/s accuracy, epoch v/s loss, and confusion matrix for SARIMA-BiLSTM respectively. Confusion matrix is a table employed to establish the prediction performance that summarizes and visualizes the model performance. The epochs v/s accuracy and loss graphs are visualizing the process when training the model.

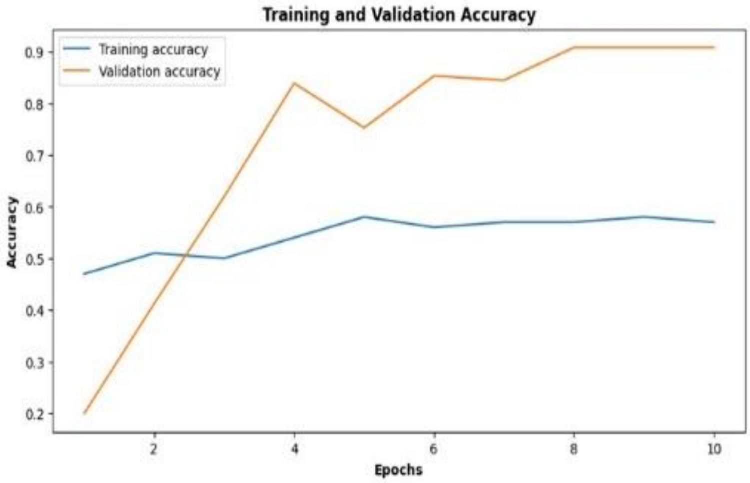

Figure 3. Epoch v/s accuracy

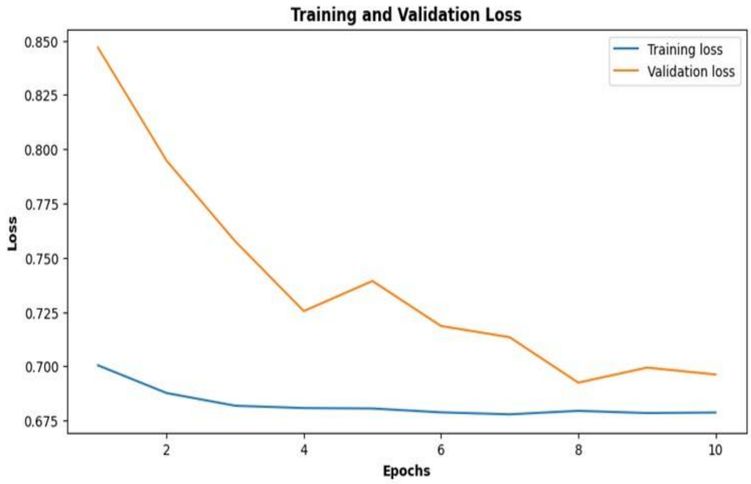

Figure 4. Epoch v/s loss

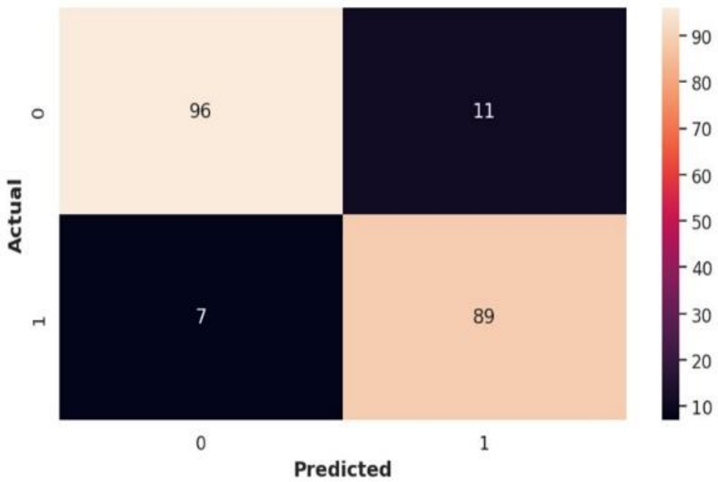

Figure 5. Confusion matrix

3.2. Comparative analysis

The SARIMA-BiLSTM is compared with existing methods through metrics like R2, MAE, MSE and RMSE shown in Table 3. The existing methods like Multilayer stacked ensemble [17], CNN-DNN [18], CEN-SCA-BiLSTM [19], and ARIMA [20] are compared with the SARIMA-BiLSTM model. The BiLSTM captures spatial features and bidirectional time dependencies from historical data which improves the model performance. The proposed SARIMA-BiLSTM is adaptable to handling a widespread of various seasonal patterns and captures spatial features. From Table 3, the SARIMA-BiLSTM attains better results through R2, MAE, MSE, and RMSE values of about 0.84, 0.056, 0.081, and 0.907 respectively.

Table 3. Comparative analysis

Method	R2	MAE	MSE	RMSE
Multilayer stacked ensemble [17]	N/A	6.63	N/A	10.545
CNN-DNN [18]	0.87	0.199	0.071	0.266
CEN-SCA-BiLSTM [19]	0.974	35.77	46.98	68.42
ARIMA [20]	0.961	N/A	N/A	0.853
SARIMA-BiLSTM	0.84	0.056	0.081	0.907

3.3. Discussion

The advantages of SARIMA-BiLSTM and the drawbacks of existing techniques are discussed in this section. The multilayer stacked ensemble [17] necessitates numerous preprocessing to fit the baseline supplies that are not initiated for yield prediction. The CNN-DNN [18] requires a significant capability of data and it cannot consider the time-series data. The CEN-SCA-BiLSTM [19] required a vast amount of captured data which is complex to obtain. In ARIMA [20], high attention was required to fascinate and stimulate farmers in coconut production. The SARIMA-BiLSTM outperforms these existing model limitations. The AS-WOA is utilized for selecting the best features which enhances the convergence rate and avoids local optima issues. The SARIMA-BiLSTM is adaptable to handling a widespread of various seasonal patterns and captures spatial features.

4. CONCLUSION

This paper proposes a SARIMA-BiLSTM for coconut yield prediction. The collected dataset is preprocessed through a label encoder and min-max normalization is employed to change non-numeric features into numerical features and enhance model performance. The preprocessed features are selected through AS-WOA which avoids local optima issues. Then, the selected features are given to the SARIMA-BiLSTM for predicting the coconut yields. The SARIMA-BiLSTM is adaptable to handling a widespread of various seasonal patterns and captures spatial features. The SARIMA-BiLSTM performance is estimated through R2, MAE, MSE and RMSE. The SARIMA-BiLSTM attains 0.84 of R2, 0.056 of MAE, 0.081 of MSE, and 0.907 of RMSE which is better when compared to existing techniques. In the future, a hybrid optimization algorithm can be employed to enhance the SARIMA-BiLSTM performance.

REFERENCES

[1] P. Singla, M. Duhan, and S. Saroha, “An ensemble method to forecast 24-h ahead solar irradiance using wavelet decomposition and BiLSTM deep learning network,” *Earth Science Informatics*, vol. 15, no. 1, pp. 291–306, Mar. 2022, doi: 10.1007/s12145-021-00723-1.

[2] B. D. Naik and M. Udayakumar, “Optimization and characterization studies on the production of bio-diesel from WSO using carbon catalyst derived from coconut meal residue,” *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 45, no. 4, pp. 9864–9879, Oct. 2023, doi: 10.1080/15567036.2019.1683096.

[3] D. Saravia *et al.*, “Yield prediction of four bean (phaseolus vulgaris) cultivars using vegetation indices based on multispectral images from UAV in an arid zone of Peru,” *Drones*, vol. 7, no. 5, May 2023, doi: 10.3390/drones7050325.

[4] S. Chinnappan, “DRIS norms for identifying yield limiting micronutrients in cocoa under coconut intercropping systems,” *Journal of Plant Nutrition*, vol. 45, no. 8, pp. 1214–1222, May 2022, doi: 10.1080/01904167.2021.1994592.

[5] R. K. Megalingam, S. K. Manoharan, D. H. T. A. Babu, G. Sriram, K. Lokesh, and S. K. Sudheesh, “Coconut trees classification based on height, inclination, and orientation using MIN-SVM algorithm,” *Neural Computing and Applications*, vol. 35, no. 16, pp. 12055–12071, Jun. 2023, doi: 10.1007/s00521-023-08339-w.

[6] M. N. Hadi, “Implementation of traditional risk management as loss prevention in coconut production results,” *AKADEMIK: Jurnal Mahasiswa Ekonomi & Bisnis*, vol. 2, no. 2, pp. 92–102, May 2022, doi: 10.37481/jmeb.v2i2.554.

[7] R. Sirisangsawang and N. Phetyim, “Optimization of tannin extraction from coconut coir through response surface methodology,” *Heliyon*, vol. 9, no. 2, Feb. 2023, doi: 10.1016/j.heliyon.2023.e13377.

[8] K. B. Hebbar *et al.*, “Predicting the potential suitable climate for coconut (*Cocos nucifera L.*) cultivation in India under climate change scenarios using the MaxEnt model,” *Plants*, vol. 11, no. 6, pp. 731, Mar. 2022, doi: 10.3390/plants11060731.

[9] B. Das, D. Murgaonkar, S. Navyashree, and P. Kumar, "Novel combination artificial neural network models could not outperform individual models for weather-based cashew yield prediction," *International Journal of Biometeorology*, vol. 66, no. 8, pp. 1627–1638, Aug. 2022, doi: 10.1007/s00484-022-02306-1.
[10] V. Mamatha and J. C. Kavitha, "Machine learning based crop growth management in greenhouse environment using hydroponics farming techniques," *Measurement: Sensors*, vol. 25, Feb. 2023, doi: 10.1016/j.measen.2023.100665.
[11] K. P. Waidyarathne, T. H. Chandrathilake, and W. S. Wickramarachchi, "Application of artificial neural network to predict copra conversion factor," *Neural Computing and Applications*, vol. 34, no. 10, pp. 7909–7918, May 2022, doi: 10.1007/s00521-022-06893-3.
[12] Z. Ahmed, P. P. Nageswara Rao, and P. Srikanth, "Area estimation of mango and coconut crops using machine learning in Hesaraghatta Hobli of Bengaluru Urban District, Karnataka," *Journal of Geomatics*, vol. 17, no. 1, pp. 85–92, Apr. 2023, doi: 10.58825/jog.2023.17.1.75.
[13] P. S. S. Gopi and M. Karthikeyan, "Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model," *Multimedia Tools and Applications*, vol. 83, no. 5, pp. 13159–13179, Jul. 2023, doi: 10.1007/s11042-023-16113-2.
[14] R. Pandiselvam *et al.*, "Central composite design, pareto analysis, and artificial neural network for modeling of microwave processing parameters for tender coconut water," *Measurement: Food*, vol. 5, Feb. 2022, doi: 10.1016/j.meafoo.2021.100015.
[15] R. E. S. Caro *et al.*, "Mining and validation of novel simple sequence repeat (SSR) markers derived from coconut (*Cocos nucifera L.*) genome assembly," *Journal of Genetic Engineering and Biotechnology*, vol. 20, no. 1, pp. 71, Dec. 2022, doi: 10.1186/s43141-022-00354-z.
[16] P. S. S. Gopi and M. Karthikeyan, "Multimodal machine learning based crop recommendation and yield prediction model," *Intelligent Automation & Soft Computing*, vol. 36, no. 1, pp. 313–326, 2023, doi: 10.32604/iasc.2023.029756.
[17] S. Iniyan and R. Jebakumar, "Mutual information feature selection (MIFS) based crop yield prediction on corn and soybean crops using multilayer stacked ensemble regression (MSER)," *Wireless Personal Communications*, vol. 126, no. 3, pp. 1935–1964, Oct. 2022, doi: 10.1007/s11277-021-08712-9.
[18] A. Oikonomidis, C. Catal, and A. Kassahun, "Hybrid deep learning-based models for crop yield prediction," *Applied Artificial Intelligence*, vol. 36, no. 1, Dec. 2022, doi: 10.1080/08839514.2022.2031823.
[19] T. Peng, C. Zhang, J. Zhou, and M. S. Nazir, "An integrated framework of Bi-directional long-short term memory (BiLSTM) based on sine cosine algorithm for hourly solar radiation forecasting," *Energy*, vol. 221, Apr. 2021, doi: 10.1016/j.energy.2021.119887.
[20] T. Prasert and V. Rungreunganun, "Thai coconut price forecasting using Arima model," *International Journal of Industrial Engineering Research and Development*, vol. 12, no. 1, 2021, doi: 10.34218/IJARET.12.1.2020.087.
[21] H. Novarianto, "Estimating coconut production and productivity of local tall in Taliabu Island using drone and sampling population," *CORD*, vol. 38, pp. 33–42, Jun. 2022, doi: 10.37833/cord.v38i.453.
[22] S. Subha and S. B. Priya, "Prediction model for a good learning environment using an ensemble approach," *Computer Systems Science and Engineering*, vol. 44, no. 3, pp. 2081–2093, 2023, doi: 10.32604/csse.2023.028451.
[23] S. Dey, P. K. Roy, and A. Sarkar, "Adaptive IIR model identification using chaotic opposition-based whale optimization algorithm," *Journal of Electrical Systems and Information Technology*, vol. 10, no. 1, 2023, doi: 10.1186/s43067-023-00102-4.
[24] C. Wang and J. Qiao, "Construction project cost prediction method based on improved BiLSTM," *Applied Sciences*, vol. 14, no. 3, Jan. 2024, doi: 10.3390/app14030978.
[25] D. G. da Silva, M. T. B. Geller, M. S. dos S. Moura, and A. A. de M. Meneses, "Performance evaluation of LSTM neural networks for consumption prediction," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 2, Nov. 2022, doi: 10.1016/j.prime.2022.100030

BIOGRAPHIES OF AUTHORS

Niranjan Shadaksharappa Jayanna is currently working as an assistant professor in the Department of Computer Science and Engineering, Kalpataru Institute of Technology, Tiptur, which is affiliated to Visvesvaraya Technological University, Belagavi, Karnataka. He can be contacted at email: niranjansj555@gmail.com.

Raviprakash Madenur Lingaraju is currently working as a professor in the Department of Computer Science and Engineering, Kalpataru Institute of Technology, Tiptur, which is affiliated to Visvesvaraya Technological University, Belagavi, Karnataka. He can be contacted at email: raviprakashml@gmail.com.