

Dual-path one-dimensional convolutional BiLSTM with attention for silk cocoon price forecasting

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ABSTRACT

Accurately forecasting silk cocoon market prices is very crucial for enhancing decision-making silk cocoon supply chain. This work introduces a hybrid deep learning model, the dual-path one-dimensional convolutional neural network–bidirectional long short-term memory with lightweight attention mechanism (DPCBLA), which combines temporal sequence data with static features to predict daily maximum silk cocoon prices. The model captures short-term temporal patterns by using a one-dimensional convolutional neural network (1D CNN) then passes to a bidirectional long short-term memory (BiLSTM) network captures long-term dependencies, and a lightweight attention mechanism that highlights key time steps for better interpretability. Static inputs such as market variety, seasonal indicators, and weather conditions are processed through a dense layer and integrated with temporal features in a dual-pathway design. The model was trained using a multi-source dataset obtained from the Ramanagara Government Silk Market in Karnataka, India. The dataset comprises historical transaction records, weather information, and seasonal disease data. The proposed model DPCBLA performed better than the traditional convolutional neural network (CNN), long short-term memory (LSTM), and BiLSTM models, achieving a mean absolute error (MAE) of 24.73, a root mean square error (RMSE) of 33.93, a mean absolute percentage error (MAPE) of 4.05, a coefficient of determination (R^2) of 0.94, and a prediction accuracy of 95.95%.

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1. INTRODUCTION

The silk cocoon market plays an important role in the sericulture sector, which tremendously affects the economic welfare of the people living in rural areas potentially relating to farmers and reelers. As the second largest producer of raw silk in the world, India contributes economically to this industry, mulberry silk acting as the major contributor to this production [1]. The correct modeling of silk cocoon prices would be required to make sound decisions, streamline supply chains, and stabilize revenues by the interest parties. However, price forecasting is not an easy task. This difficulty arises because agricultural markets are volatile and exhibit non-linear behaviors. Furthermore, these markets are heavily subject to seasonal, demand-supply, and climate-related fluctuations [2].

Generalized autoregressive conditional heteroskedasticity (GARCH) have acted as a volatility model whereas autoregressive integrated moving average (ARIMA) and multiple ARIMA have been extensively used as price volatility models in silk cocoon markets. As an example, one can mention the study by Halagundegowda *et al.* that showed the GARCH (3, 2) model to be more effective than the artificial neural networks (ANN) in forecasting bivoltine prices of cocoon volatility, emphasizing the necessity of clustering volatility in price series modeling [3], [4]. In parallel, time series decomposition and quadratic trend models have equally been used to obtain seasonal and moving average components of prices of mulberry cocoons, which reasonably have resulted in forecasting ability [5].

Artificial intelligence (AI) has been applied in sericulture, to analyze the prices and identify disease, sorting cocoon and climate-resistant production, which can be enhanced to increase productivity and supply chain further as seen in [6]–[9]. At the same time, historical price forecasting research studies have been widely founded on conventional statistical techniques or basic neural networks, such as backpropagation-based networks [10]. Not limited to the price forecasting use case, AI-based solutions have been created to assist sericulture in recognizing disease and cocoon quality. efficient network variant B3 (EfficientNetB3) as a deep learning model has been effectively used to identify silkworm diseases using images and environmental monitoring in order to advise farmers on rearing in real-time thus increasing yield and decreasing loss in cocoons produced [11]. Such inclusion of vision-based diagnosis of the diseases and the inclusion of climate intelligence represent the rising importance of AI in smart sericulture [12].

Production of raw silk varies with the grade of cocoon and some proposed automated sorting using computer vision and machine learning are supposed to increase the efficiency. The came up with a vision-and-Terahertz spectrum based defective cocoons recognition system which is applicable in the Terahertz spectral data and deep learning based mask-based object detection that was able to detect the most common defect of cocoons with high accuracy (mean average precision (mAP) of as much as 99.25%), which introduces intelligent picking and sorting in the production lines [13]. Deep learning has been used to benefit terahertz imaging in a speedy identification of the stages of growth of silkworm egg, the variability of AI in sericulture research [14]. Moreover, the *Bombyx mori* cocoon sorting automated prototypes are created to forecast the supply and demand of silk considering the export-import data, and lastly the significance of AI in terms of market intelligence and supply chain management is also realized [15]–[17].

With the advances in deep learning, one-dimensional convolutional neural networks (1D CNNs) have become a useful technique to extract short-term local patterns in time-series data. They simply discover relevant features by convolving across input sequences with several filters [18]. The modular system in which convolutional neural network (CNN) was combined with preprocessing and pattern recognition of crop information in the agricultural sphere. CNN layers have also proven to have positive effects in preceding long short-term memory (LSTM) layers because it helps to remove noises by highlighting important signals [19].

Recent studies have demonstrated the growing effectiveness of combining CNN with bidirectional long short-term memory (BiLSTM) networks and attention mechanisms for handling complex sequential data. The BiLSTM model that augmented attention significantly improved the recognition of personality from user-generated content by allowing the network to emphasize critical parts of input [20], [21]. Expanding this idea, the proposed the combination of CNN, BiLSTM, and an attention mechanism to implement a model to predict personality characteristics using user actions on social networks [22]. In their findings, the hybrid model captured spatial and time trends well and hence was more accurate in prediction. In addition, another work done [23] on CNN-BiLSTM with the attention model to map the precipitation process every day showed that the attention mechanism has the ability to isolate and emphasize vital time steps in the time series, enhancing the predictability of the model [24]–[26].

Despite the recent advances, there is still a gap in research combines temporal and static features to make accurate predictions of prices of silk cocoons. The combination models of CNN, BiLSTM, and the attention mechanisms have demonstrated good performance in predicting the financial data as they are able to capture short-term patterns and long-term trends. Building on this idea, our work proposes a new model dual-path one-dimensional convolutional neural network–bidirectional long short-term memory with lightweight attentionmechanism (DPCBLA). The hybrid model is conceived specifically to the silk cocoon market and can positively contribute to price forecasting with the two types of data and to the extent of benefiting farmers, traders, and other stakeholders.

2. METHOD

This section explains how the data was collected and prepared before training the model. It also walks through the key components of the proposed DPCBA model, which is designed to predict the prices of silk cocoons. The model offers a combination of three key techniques, 1D CNN, BiLSTM, and an attention mechanism. Measures for evaluating the performance of models are also discussed.

2.1. Data collection and preprocessing

To develop an accurate forecasting model for silk cocoon prices, the data was taken based on three main sources also referred to as the most credible ones. At first, historical data on daily transactions of the Ramanagara Government Silk Market in the Karnataka Indian state during the period of March 1, 2021 to September 21, 2024 were utilized. These records contained cocoon varieties, quantities sold, rates and volume of a transaction, and this was the core data of study of the market trends [27]. Second, the historical weather data of Ramanagara, including temperature, humidity, rainfall, and other metrics, were acquired with the help of the weather underground, which is one of the well-known sources of climate-related information [28]. These weather conditions have major impacts to the rearing of silkworms and consequently prices of cocoons. Third, information on the seasonal occurrence of major silkworm diseases, including Grasserie, Flacherie, Muscardine, Pebrine, and the Uzi fly, was obtained from recent peer-reviewed literature on sericulture disease diagnostics and management. These diseases are recognized as major biological factors affecting cocoon quality, silk production, and market price fluctuations [29], [30]. The combination of the market activity, the environmental setting and the incidence of diseases provides a rich database to assist in modeling reality prices.

The collected data was preprocessed to prepare it for deep learning-based forecasting. The date column was converted into the form of datetime so that the characteristics including year, month, day, and day of the week could be extracted because they played an important role in determining seasonality and trends. The data was organized into three input sets meant to be used in inputting the temporal inputs (e.g., daily traded quantity and maximum rate), the static inputs (e.g., averages of previous year, weather physical indicators, cocoons types, diseases, and calendar characteristics), and the target variable (maximum daily price). MinMax scaling was applied on each group of feature to eliminate variability and speed training. The sliding window methodology with 10-days sequence was used to obtain training samples. Each of those samples employed 10 days of time series data and corresponding time-independent characteristics to forecast the maximum price on the following day. With such a technique, the model was able to learn both short and long patterns as well as contextual factors improving accuracy of prediction.

2.2. One-dimensional convolutional neural network

The classic 1D CNN architecture normally includes convolutional layers, pooling layers, and full-connected layers. The convolutional layers use various filters to identify patterns, and pooling layers decrease the dimensionality of the results in order to preserve an important signal and drop the unwanted ones. Then the features side by side are finally fed into the fully connected layers whose work is to make predictions or classifications based on the representations it learns. Figure 1 shows a classical architecture of a 1D CNN adopted in time-series modeling.

In this work, temporal features are extracted from cocoon market data including quantity and max rate, using a 1D CNN consisting of three stacked groups of convolutional blocks with 128 filters for each group. Every convolutional block helps the network recognize progressively more complex patterns that help with forecasting. A single convolutional block is shown in (1).

$$Z^{(1)} = \text{Pool} \left(\sigma \left(X * W^{(1)} + b^{(1)} \right) \right) \quad (1)$$

Here, the time series data are processed by means of an input matrix X and $W^{(1)}$ represents the convolutional filter weights in the first block (with 128 filters) together with biases $b^{(1)}$, $*$ denotes the one-dimensional convolution operation, $\sigma(\cdot)$ is the rectified linear unit (ReLU) activation function applied element-wise to introduce non-linearity and down-samples the output by using max pooling denoted $\text{Pool}(\cdot)$. The convolution step allows each filter to slide across the input sequence, identifying significant temporal variations and local patterns. It is the activation function that allows the network to deal with non-linear relations and the pooling step does this by removing extra features and cutting back on overfitting. The process continues for the second and third convolutional blocks, so that each layer both abstracts and improves

the feature maps made by the preceding block. The output produced after processing the model includes compressed, rich information from the original series that allows the model to understand the changes, cycles and unusual trends in the cocoon market.

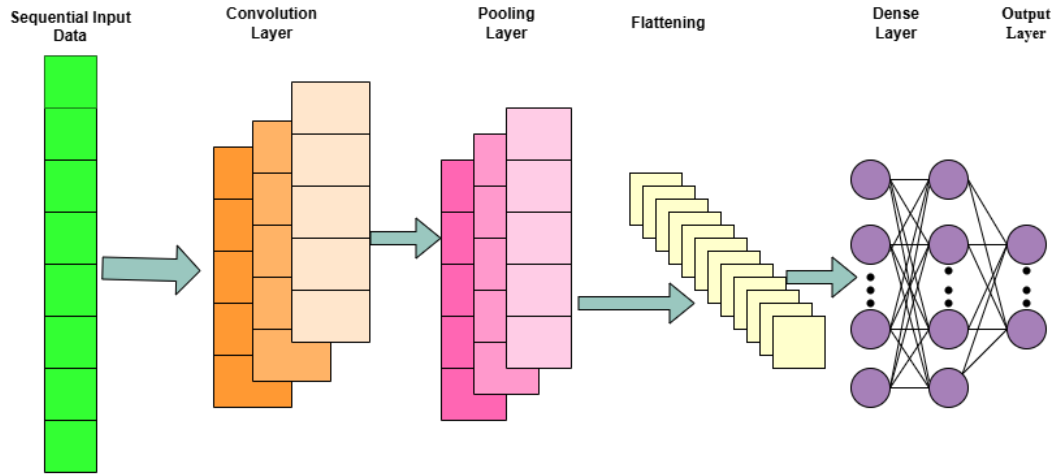


Figure 1. The classical structure of 1D CNN

2.3. Bidirectional long short-term memory

The BiLSTM models takes the input sequence in both directions at once and concatenating them together. The forward layer detects the patterns between past and present, and another layer detects the information between future and the past. The hidden states of the both directions are calculated at each time step and combined into a model of a fuller and context-sensitive structure. In mathematical terms this can be explained in (2).

$$h_t = h_t^{\text{forward}} \oplus h_t^{\text{backward}} \quad (2)$$

Where h_t^{forward} is the hidden state from the forward LSTM, h_t^{backward} is the hidden state from the backward LSTM, and $\oplus$ denotes element-wise concatenation. BiLSTM's ability to combine past and future data makes it more effective in learning about complicated temporal connections, especially important for capturing market price shifts brought about by environmental and economic signals reaching the market late. This allows BiLSTM to use information from both past and future at the same time which helps it better capture the relationship between historic data and quarterly market risks from delays in information from environmental and economic factors. In this model, the BiLSTM layer is the most important for handling the sequence of cocoon transaction amount and price per day. Using both future and past information, the model highlights patterns in climate, seasonal changes and disturbances to sericulture. When we combine this with convolutional layers that pick out spatial and static details from the input, our forecasts become more accurate as well.

2.4. Attention mechanism

Generally in time series forecasting the most common architectures such as LSTM and BiLSTM can find it challenging to represent all necessary temporal dependencies because of the fixed-size context vectors and the subsequent information bottleneck, particularly when long input sequences are being used. In order to address these problems, the attention mechanism gets used, which lets the model dynamically pay attention to the most important part of the input sequence assigning different time steps different levels of importance. This mechanism involves calculation of context vector which sums up all the hidden states of the encoder-like BiLSTM depending on their importance in relation to the present forecast. All hidden states are proportionally contributing based on what it has learned and this enhances the accuracy of forecast by the model and meaningful sense to the model by finding out which inputs are highly impacting the result. Given the encoder hidden states $h_1, h_2, \dots, h_T$, the attention score e_t for each hidden state h_t is calculated in (3).

$$e_t = \mathbf{u}^T \cdot \tanh(W_h h_t + W_s s_{t-1} + b_e) \quad (3)$$

Where W_h , W_s , and u are learnable weight matrices and vector, s_{t-1} is the hidden state of the previous decoder and b_e is a bias term. The attention weights α_t are then derived using the softmax function as shown in (4).

$$\alpha_t = \text{Softmax}(e_t) = \frac{\exp(e_t)}{\sum_{j=1}^T \exp(e_j)} \quad (4)$$

These weights are used to compute the context vector c as a weighted sum of the encoder hidden states as shown in (5).

$$c = \sum_{t=1}^T \alpha_t \cdot h_t \quad (5)$$

Finally, this context vector c is concatenated with the current decoder hidden state and passed through a fully connected layer to produce the final output prediction.

2.5. Proposed dual-path 1D CNN–BiLSTM with lightweight attention mechanism

In this paper, the structure of the DPCBLA model is proposed for forecasting silk cocoon market prices by effectively capturing both temporal input features (e.g., quantity and historical max rate) and static input features (e.g., market variety, weather indicators, and seasonal disease). The proposed model algorithm and architecture shown in Figure 2 and Algorithm 1. The architecture integrates three powerful components: 1D CNN, BiLSTM, and lightweight attention mechanism. The 1D CNN layer acts as the initial temporal feature extractor and employs 128 filters with a kernel size of 3 to capture localized temporal patterns in the sequential input data. This layer is responsible for extracting essential short-term trends and dependencies from a 10-day sliding window of historical observations. This is followed by a MaxPooling1D layer that reduces dimensionality by selecting the most dominant values, thus simplifying the representation while retaining essential information.

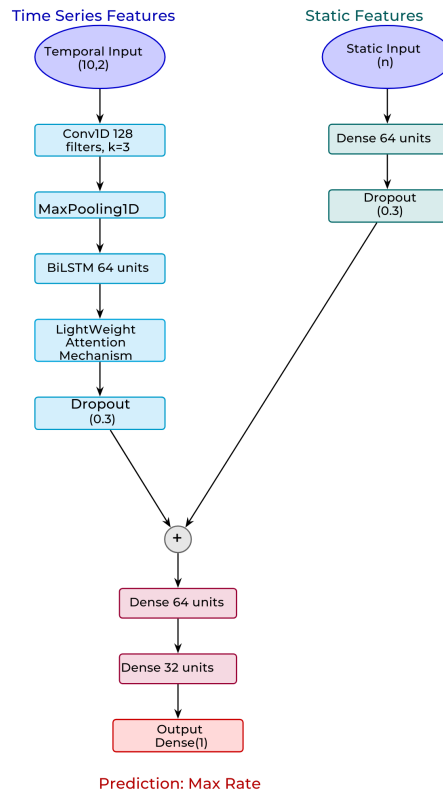


Figure 2. Proposed dual-path 1D CNN–BiLSTM with lightweight attention mechanism architecture

The output of the CNN model is passed into a BiLSTM layer, which processes the data in both forward and backward directions, allowing the model to capture dependencies across both past and future time steps, which is critical for understanding market behavior. After the BiLSTM layer, a custom lightweight attention mechanism is applied to dynamically assign importance scores to the sequence outputs, enabling the model to focus more on the most influential parts of the input sequence. This improves the interpretability and prediction accuracy of the model. Dropout layers with a dropout rate of 0.3 are added to prevent overfitting by randomly deactivating 30% of the neurons during training. In parallel, static features (non-sequential data such as market type or seasonality indicators) are passed through a dense layer and then combined with the temporal features derived from the CNN–BiLSTM–attention pipeline. The concatenated features are passed through fully connected dense layers to integrate and map them to the final output prediction, which is the future maximum rate of silk cocoon prices.

2.6. Model evaluation

To evaluate the performance of the deep learning models used for forecasting, several well-known regression-based metrics were applied. This study uses mean absolute error (MAE), root mean square error (RMSE), coefficient of determination (R^2), mean absolute percentage error (MAPE), and accuracy. The proposed model is also compared with other deep learning models such as DPCBLA, 1D CNN+BiLSTM, BiLSTM, 1D CNN+LSTM, LSTM, 1D CNN, AR-GARCH, and quadratic trend.

Algorithm 1 DPCBLA: dual-path 1D CNN–BiLSTM with lightweight attention

Require: Dataset $D = \{(x_t, s_t, y_t)\}_{t=1}^T$, sequence length L , batch size B , learning rate α

T : Total number of time steps in the dataset

$x_t \in \mathbb{R}^n$: Temporal input features at time t

$s_t \in \mathbb{R}^m$: Static input features at time t

$y_t \in \mathbb{R}$: Target value (Max rate) at time t

1: Data preprocessing:

2: Remove missing or erroneous records from D

3: Normalize temporal features x_t , static features s_t , and target y_t using MinMaxScaler

4: Sequence generation:

5: **for** $i = 1$ to $T - L$ **do**

6: $X^{(i)} \leftarrow [x_i, x_{i+1}, \dots, x_{i+L-1}]$

7: $S^{(i)} \leftarrow s_{i+L}$

8: $Y^{(i)} \leftarrow y_{i+L}$

9: **end for**

10: Split $\{X^{(i)}, S^{(i)}, Y^{(i)}\}$ into training, validation, and test sets

11: **Model architecture**

12: *// Temporal path*

13: $H_1 \leftarrow \text{ReLU}(\text{Conv1D}(X, \text{filters} = 128, \text{kernel} = 3))$

14: $H_2 \leftarrow \text{MaxPool1D}(H_1, \text{pool} = 2)$

15: $H_3 \leftarrow \text{BiLSTM}(H_2, \text{return_sequences}=\text{True})$

16: *// Lightweight attention*

17: $e_t = \tanh(H_3 W + b)$

18: $\alpha_t = \text{softmax}(e_t)$

19: $R = \sum_{t=1}^L \alpha_t H_3^{(t)}$

20: $R_d \leftarrow \text{Dropout}(R, p = 0.3)$

21: *// Static path*

22: $S' \leftarrow \text{ReLU}(\text{Dense}(S, \text{units} = 64))$

23: $S_d \leftarrow \text{Dropout}(S', p = 0.3)$

24: *// Fusion and output*

25: $z \leftarrow \text{Concatenate}(R_d, S_d)$

26: $z' \leftarrow \text{ReLU}(\text{Dense}(z, \text{units} = 64))$

27: $z'' \leftarrow \text{ReLU}(\text{Dense}(z', \text{units} = 32))$

28: $\hat{y} \leftarrow \text{Dense}(z'', \text{units} = 1)$

3. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed DPCBLA model in forecasting the maximum daily price of silk cocoons (Max rate). A comparison was conducted with five other models: 1D CNN, LSTM, BiLSTM, 1D CNN+LSTM, and 1D CNN+BiLSTM. Figures 3 to 8 illustrate the prediction results, where the horizontal axis represents the number of days, and the vertical axis shows the max rate. The solid blue line in both figures indicates the true prices of cocoons whereas the solid orange line shows the forecast values of each model. The nearer the orange line approaches the blue line, the more efficient the model works. The DPCBLA model among the six models was closest to the actual-trend of price in terms of the approach applied, and it always showed a smaller deviation, which proves the overall high performance of the hybrid model to track local patterns (CNN), long-term dependencies (BiLSTM), and significant temporal characteristics (attention mechanism) and apply when forecasting the maximum values of silk cocoon prices in the chosen dataset.

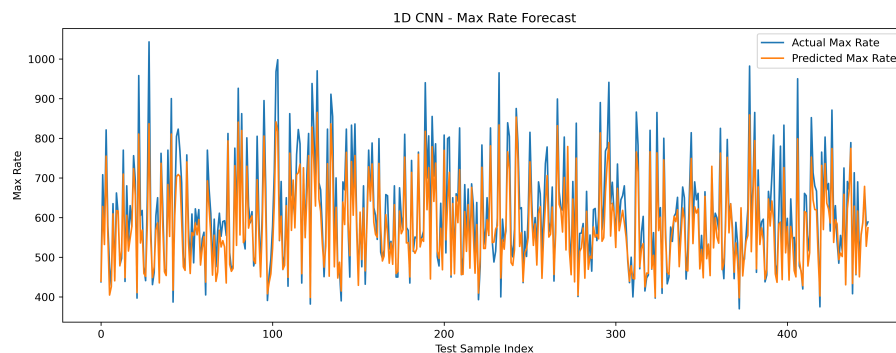


Figure 3. Prediction silk cocoon max rate based on 1D CNN model

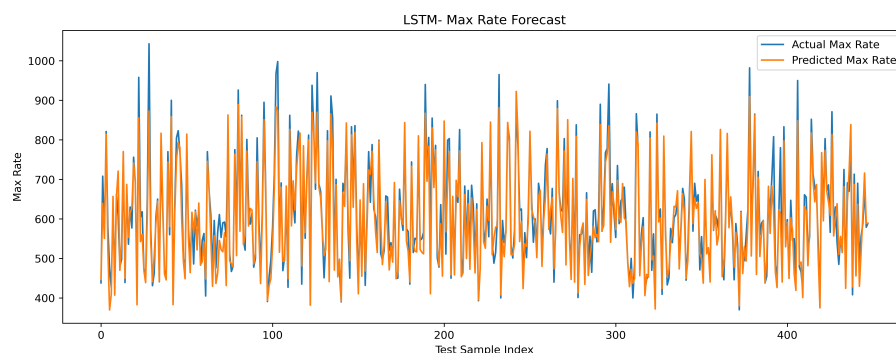


Figure 4. Prediction silk cocoon max rate based on LSTM model

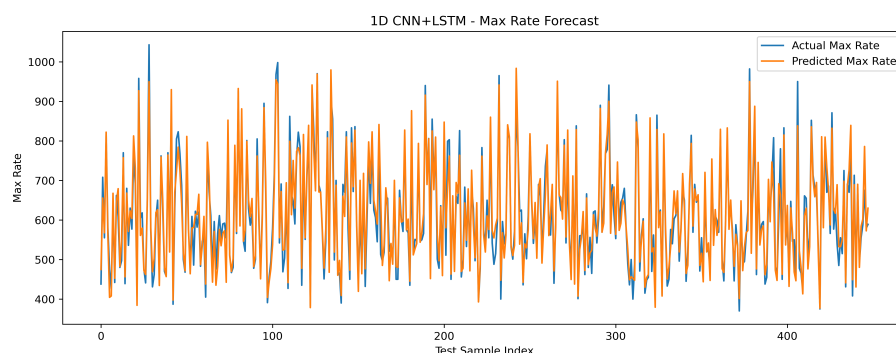


Figure 5. Prediction silk cocoon max rate based on 1D CNN+LSTM model

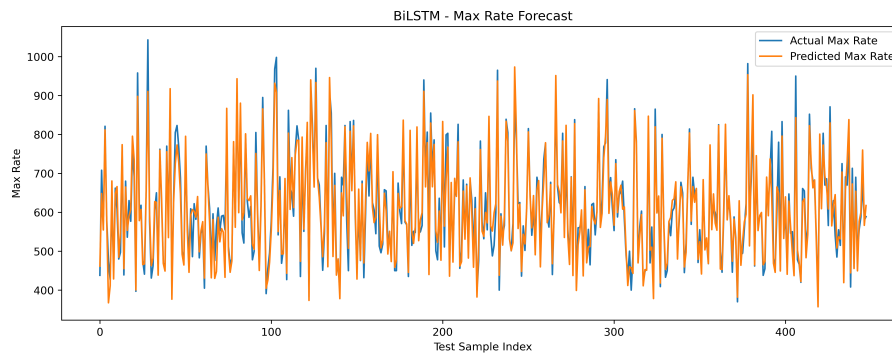


Figure 6. Prediction silk cocoon max rate based on BiLSTM model

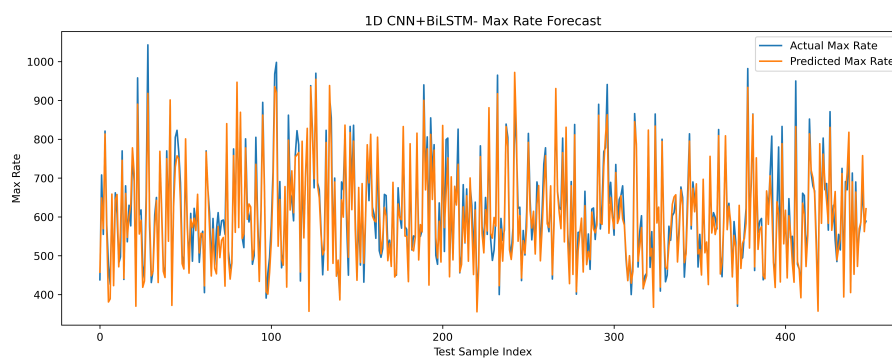


Figure 7. Prediction silk cocoon max rate based on 1D CNN + BiLSTM model

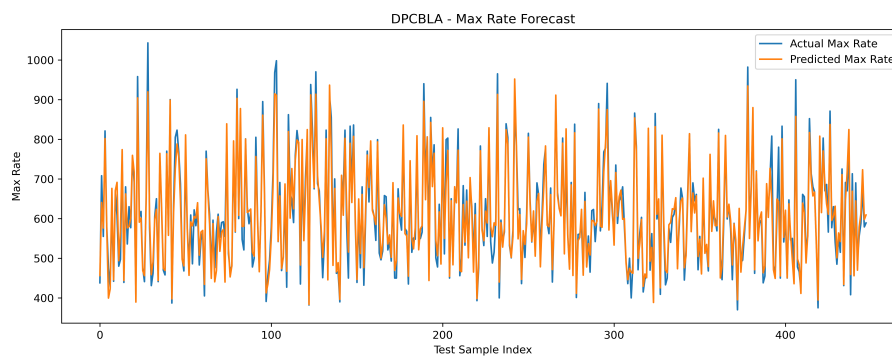


Figure 8. Prediction silk cocoon max rate based on DPCBLA model

As shown in Figure 8 and compared to the prediction results illustrated in Figures 3 to 7 the proposed DPCBLA model consistently outperformed the other five models in forecasting the maximum price of the silk cocoon market. Its prediction curve closely followed the actual market trend, demonstrating strong alignment with real values and reflecting high forecast accuracy. Conversely, comparing the single 1D CNN and LSTM models, there was a large discrepancy between the predicted and the actual prices of silk cocoon, which results show that neither of the models can be independent enough to predict the complex dynamics of the silk cocoon prices. The hybrid version of 1D CNN + LSTM provided a slight advancement of individual models, but did not impress regarding the accuracy of the prediction, a slight convergence in prediction was achieved.

The model 1D CNN + BiLSTM got better results, and the prediction curve followed the real price patterns more accurately, which allows concluding that it understands temporal dependencies in a better way. But the DPCBLA model is definitely the most successful in all of them. Its excellence should be

attributed to the consideration of the attention mechanism that enables the model to pay attention to the most significant characteristics that considerably increase its prediction potential. Moreover, BiLSTM bidirectional architecture allows learning from future and past time steps and adds another dimension to feature extraction and causes increased accuracy in forecasting. Together, spatial pattern recognition, temporal learning, and feature prioritization make the proposed model very intelligent in capturing the non-linear dynamic response of the silk cocoon market.

Table 1 presents the performance evaluation measures for all six models, including MAE, RMSE, R^2 , MAPE, and accuracy. Table 1 shows the best performing values in bold form to allow for easy comparison. The DPCBLA model had the best scores when looking at R^2 and how well it generally made the correct prediction which was really low and this means that it is doing a very good job of fitting the actual data in the market. In addition, it had the lowest scores on MAE, RMSE, and MAPE, which means that it can better eliminate prediction error than the rest of the baseline models. These findings show clearly that the proposed hybrid model is a better model and much more reliable in predicting silk cocoon prices.

Table 1. Model performance comparison for max rate forecasting

Model	MAE	RMSE	R^2	MAPE (%)	Accuracy (%)
DPCBLA	24.73	33.94	0.94	4.05	95.95
1D CNN + BiLSTM	25.04	34.18	0.94	4.10	95.85
BiLSTM	25.11	34.35	0.94	4.15	95.56
1D CNN + LSTM	26.70	35.56	0.93	4.44	94.97
LSTM	27.51	37.10	0.93	4.75	94.05
1D CNN	28.41	38.27	0.92	7.20	92.74

As shown in Table 1, the performance of the DPCBLA model is closely followed by the 1D CNN+ BiLSTM model, making it the next best among the compared approaches. However, when we examine the metrics more closely, the proposed model demonstrates consistent improvements across all major indicators. The proposed model will show a decrease of 1.24 units in the MAE compared to the 1D CNN + BiLSTM model. In the case of the RMSE, the decrease is 0.70 making it fit better with the actual values. On the same note, an efficiency of a 1.22% decrease in MAPE also shows even further inside the enhanced accuracy of its prediction. Though comparatively small (0.10%), the improvement of the accuracy in relation to the 1D CNN model with the BiLSTM model is still noted as the step towards it. Both models are characterized by the same R^2 that indicates that they can explain the same amount of variance in the data, but it is possible to note that the overall decrease in the errors indicates that the integration of the attention mechanism has contributed to the fine-tuning of the predictions. Such small gains speak in favor of the idea to use lightweight attention layers to make the model more able to identify and concentrate on the most important features, which turned out to be useful in terms of better performance in forecasting prices of silk cocoons.

Table 2 compares the proposed DPCBLA model with representative silk cocoon price forecasting approaches reported in the literature. The ARIMA model achieved an R^2 value of 0.91 with a MAPE of 5.57% for the Ramanagaram market and an R^2 value of 0.89 with a MAPE of 7.70% for the Siddlaghatta market [3]. Similarly, the autoregressive (AR)–GARCH model reported an R^2 value of 0.89 and a MAPE of 5.68% for the Ramanagaram market [4], while the quadratic trend model achieved an R^2 value of 0.87 with an RMSE of 4.04 for the Kaliachak market in West Bengal [5]. Whereas random forest model for the Ramanagara market reported an MAE of 2965.14, an RMSE of 5985.60, and an R^2 value of 0.0903 under a leakage-free early forecasting setting [31]. Results shows that the proposed DPCBLA model achieved an MAE of 24.73, an RMSE of 33.94, an R^2 value of 0.94, and a MAPE of 4.05%. These results indicate that integrating a 1D CNN, a BiLSTM network, and a lightweight attention mechanism effectively captures complex temporal dependencies and improves forecasting performance.

Table 2. Comparison of the proposed model with existing silk cocoon price forecasting studies

Model	Market/Dataset	MAE	RMSE	R^2	MAPE (%)	Ref.
ARIMA	Ramanagaram, Karnataka, India	5.50	10.96	0.91	5.57	[3]
ARIMA	Siddlaghatta, Karnataka, India	6.50	11.82	0.89	7.70	[3]
AR–GARCH	Ramanagaram, Karnataka, India	–	–	0.89	5.68	[4]
Quadratic trend	Kaliachak, West Bengal, India	–	4.04	0.87	–	[5]
Random forest	Ramanagara, Karnataka, India	2965.14	5985.60	0.0903	–	[31]
Proposed DPCBLA	Ramanagara, Karnataka, India	24.73	33.94	0.94	4.05	This work

4. CONCLUSION

In this study develops a hybrid model DPCBLA designed to improve the accuracy of the forecasting of silk cocoon prices. Model enables using two paths: one path, using temporal input data set, processes through to 1D CNN to capture short term patterns, and then processes through to BiLSTM to learn long term dependencies. A lightweight attention mechanism is then used to select the most relevant features. Concurrently, the second path employs on cocoons types, seasonal and weather conditions. This architectural feature enhances the model's effectiveness by integrating various data types, providing stakeholders with more accurate and dependable price forecasts in the silk sector. In order to test the effectiveness of the model, it was contrasted to some baseline approaches. The model proposed recorded small values of error with MAE at 24.73, RMSE at 33.93, and MAPE at 4.05%, and better performance measures in the form of R^2 at 0.94 and accuracy at 95.95%, which are more efficacious than the other models tried. These findings evidence the high potentiality of such a model in eliminating prediction error and the high similarity with real market trends. Future research could explore evolutionary algorithms for enhanced robustness and adaptability.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal Analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : **O**riginal Draft

E : **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject Administration

Fu : **F**unding Acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SS], upon reasonable request.

INFORMED CONSENT

Not applicable, as this study did not involve human participants or personally identifiable information.

ETHICAL APPROVAL

Not applicable, as this study did not involve human or animal subjects and used only non-sensitive computational or public data.

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