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A COMPARATIVE STUDY OF DEEP LEARNING MODELS FOR COTTON PRICE FORECASTING IN GUJARAT, INDIA

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ABSTRACT

Forecasting agricultural prices is exceptionally difficult because of the unpredictable global weather events, influential role of government policies, evolving consumer preferences and technology. This study focuses on the impact of price forecasting in the agricultural sector, specifically within the cotton industry. Accurate predictions of cotton prices are of most important to various stakeholders, including cotton farmers, textile mills and shippers. To enhance forecasting accuracy, this research employs advanced machine learning techniques such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), as well as stacked LSTM models. These models are trained and evaluated using statistical metrics like RMSE, MAPE, SMAPE and MAE. Notably, the stacked LSTM model consistently outperforms other models, demonstrating superior predictive performance with minimal errors. This study also highlights the stacked LSTM's ability to effectively capture long-term data dependencies, leading to significantly improved prediction precision.

Keywords: ANN, RNN, GRU, LSTM, Stacked LSTM and price forecasting

INTRODUCTION

Cotton stands as a pivotal cash crop and a vital fiber in the agricultural landscape of India, which holding a dominant position in both the country's industrial and agricultural sectors. Often referred to as "White-Gold," cotton is an essential raw material for textile production. India holds the second position worldwide for cotton consumption, export and production, having production of

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5.84 million metric tonnes. China stands as the primary producer, generating 5.89 million metric tonnes, trailed by the USA with 3.15 million metric tonnes, Brazil with 3.02 million metric tonnes and Pakistan with 0.85 million metric tonnes [3]. India contributing approximately 26% to the world's cotton production [1]. Indian cotton industry supports around 6 million cotton farmers and serves as a livelihood source for 40-50 million workers. Notable cotton-producing nations include China, the USA, Pakistan, Brazil, Australia, Uzbekistan, Turkey, Turkmenistan and Mexico [2]. Among the top 5 countries of production [3], India is alone contributing 31% to the world's cotton production.

Also, within India, Gujarat is the leading producer of cotton with the production of 87.12 lakh bales of cotton [4], followed by Maharashtra (81.85 lakh bales), Telangana (54.41 lakh bales), Rajasthan (25.51 lakh bales) and Karnataka (20.93 lakh bales) during 2022-23. Maharashtra has the largest area under cotton cultivation, covering 42.29 lakh hectares, followed by Gujarat with 25.49 lakh hectares and Telangana with 20.24 lakh hectares.

Cotton is a crop grown worldwide. Which is prone to substantial price variations influenced by global economic fluctuations. The fluctuations in prices present potential risks to individuals and entities involved in cotton production and distribution, including producers, suppliers, consumers and other stakeholders. Therefore, the need to predict cotton prices becomes highly significant. Numerous researchers have explored statistical models for agricultural price forecasting such as applications of ARIMA model for agricultural price forecasting [5]. Investigation of model in agricultural price forecasting [6]. Forecasting horticultural products price [7], Oil palm price [8], Tomatoes price [9], Maize price [10], Paddy price [11], Onion price [12], Pulse price [13] and Natural Rubber price [14]. These studies primarily concentrated on the prediction of prices, serving as a valuable resource for market traders, farmers and policymakers.

Multiple researchers have utilized the ARIMA model in diverse agricultural domains for predictive purposes, such as forecasting agricultural productivity [15], wheat area and production [16], livestock products consumption [17], maize production [18], potato production [19]. The technique of time series forecasting involves analysing historical patterns within a series of data points to anticipate future price trends. Apart from traditional time series models, recent studies demonstrate an increasing interest in employing deep learning algorithms, notably Artificial Neural Networks (ANN) in various agricultural predictions. These include the utilization of ANN for wheat yield prediction [20], ANN for predicting area, production and productivity of sapota in Gujarat [21], Forecasting area, production and productivity of citrus in Gujarat by using GARCH, GARCH and TAR models [22], Forecasting models for predicting pod damage of pigeon pea in Varanasi region [23], Forecasting of Early Maturing Pigeon pea Yield for Central Zone of India [24], Forecasting of Losses Due to Pod Borer, Pod Fly and Yield of Pigeon pea for Central Zone

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of India by Using Artificial Neural Network [25], Sugarcane yield forecasting using ANN models [26], An artificial neural network approach for predicting area, production and productivity of Banana in Gujarat [27]. Using deep learning techniques prediction of fruit production [28], Yield forecasting of Maize by linear regression and artificial neural networks [29], Corn price forecasting [30], Choosing an accurate cacao price forecasting model [31], Price forecasting of coriander [32], Recurrent neural network algorithm for forecasting banana prices [33], Moreover, a variety of Deep learning based models: Basic LSTM, Bi LSTM, Stacked LSTM, CNN LSTM and Conv LSTM were used to forecast Agricultural commodities prices [34], A CNN-Bidirectional LSTM Approach for Price Forecasting of Agriculture commodities in Gujarat [35], Forecasting agricultural commodities prices using deep learning-based models: basic LSTM, bi-LSTM, stacked LSTM, CNN LSTM, and convolutional LSTM [36], Deep long short-term memory-based model for agricultural price forecasting [37], significance of deep learning techniques is highlighted in [38-39]. To forecast cotton prices, we've exclusively focused on machine learning algorithms.

The area of Artificial Intelligence (AI) known as Deep Learning (DL) enables computers to learn and enhance their performance without requiring explicit programming. These models utilize historical data exclusively to learn the probabilistic relationship between past observations and future outcomes. The main objective of this research is to forecast the cotton price in Gujarat, India. To achieve this, various neural network models, including ANN, RNN, GRU, LSTM and stacked LSTM, are employed rather than statistical techniques because of many empirical studies indicating the superior performance of machine learning algorithms [40] over statistical methods. However, an issue in prior research was the utilization of weekly or monthly data, potentially failing to accurately depict daily price fluctuations. In response, our investigation centres on daily data, spans from April 2002 to April 2023 to ensure a more accurate representation of cotton price changes. Our aim is to address the real-world challenge of delivering more precise cotton price predictions, which can aid farmers, traders and policymakers in making well-informed choices. The research seeks to determine the forecasting model that offers the most accurate predictions, which will be evaluated using performance metrics like RMSE, MAPE, SMAPE and MAE.

MATERIALS AND METHODS

Data collection

The time-series data sourced from AGMARKNET https://agmarknet.gov.in/SearchCmmMkt.aspx?Tx_Commodity=15&Tx_State=GJ&Tx_District=11&Tx_Market=64&DateFrom=1-April-2000&DateTo=21-April-2023&Fr_Date=1-April-2000&To_Date=21-April-2023&Tx_Trend=0&Tx_CommodityHead=Cotton&Tx_StateHead=Gujarat&Tx_DistrictHead=

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Rajkot&Tx_MarketHead=Rajkot regarding the daily modal cotton prices spanning from 2002 to 2023 was gathered from the Rajkot District market in Gujarat, India. Rajkot Market was chosen as the representative market because it has the highest level of cotton arrivals. The dataset covers the period from April, 2002 to April, 2023 and comprises 7696 observations.

Methodology

Following analytical models were used in this study:

Deep learning techniques

In artificial intelligence, deep learning focuses on teaching neural networks to recognize complex data patterns and make predictions.

Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) aim to replicate the intelligence of the human brain in machines. They are biologically motivated and possess several salient features such as being data-driven, self-adaptive, inherently non-linear and universal functional approximators. ANNs typically consist of three layers: The Input layer, Hidden layers and Output layer, with interconnected neurons, as shown in Fig 1.

When creating ANN models, it is crucial to take into account factors like the quantity of input vectors, layers, output vectors and neurons.

ANN model Equation for the ϕ_r value based on trained neural network [41]:

$$\phi_{rn} = f_{Sig}\left\{b_0 + \sum_{k=1}^{h}[W_k f_{sig}(b_{hk} + \textstyle\sum_{i=1}^{m} \omega_{ik} x_i)\right\} \ldots . (1)$$

Where ϕ_{rn} is the normalized (in the range -1 to 1 in this case) ϕ_r value

b_0 is bias at the output layer

W_k is connection weight between kth neuron of hidden layer and the single output neuron

b_{hk} is bias at the kth neuron of hidden layer

h is number of neurons in the hidden layer

ω_{ik} is connection weight between ith input variable and kth neuron of hidden layer

x_i is normalized input variable i in the range [1,1] and f_{Sig} is sigmoid transfer function.

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Typically, the logistic sigmoid function. denoted as $g(x) = \frac{1}{1+e^{-x}}$ is employed as the non-linear activation function. Alternatively, various other activation functions like linear, hyperbolic tangent, Gaussian and so on can be employed. [42].

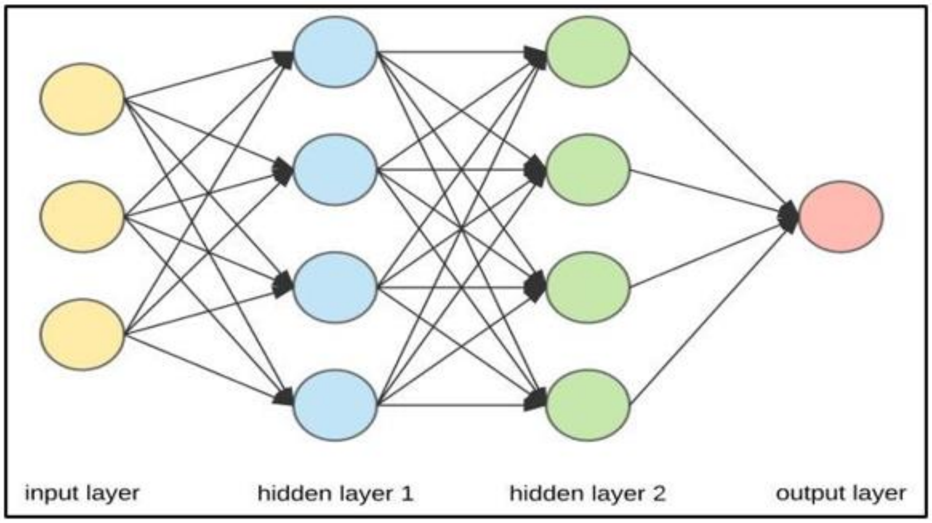

Fig 1: Artificial Neural Network Architecture [45]

Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNNs) are a specialized form of Artificial Neural Networks (ANNs) that process sequences over time. They've evolved from traditional feedforward neural networks and possess internal memory, allowing them to handle varying sequence lengths [43]. This is achieved by establishing connections between nodes at consecutive time steps, introducing a time-dependent aspect to the model.

At each time point, t, nodes with recurrent connections receive input from both the current data point, $x(t)$ and the hidden node values $h(t-1)$, which represent the network's previous state. The output, $\hat{y}(t)$ at a time t, depends on the hidden node values $h(t)$ at that moment. It's worth noting that the input, $x(t-1)$, from the prior time step, t – 1, can have an impact on the output, $\hat{y}(t)$, at time t and this influence subsequently travels through these recurrent connections [44]. The following computations illustrate the forward step.

$$h_{(t)} = \sigma(W_{hx}x_{(t)} + W_{hh}h_{(t-1)} + b_h) \quad \ldots(2)$$

$$\hat{y}_{(t)} = softmax(W_{yh}h_{(t)} + b_y) \quad \ldots(3)$$

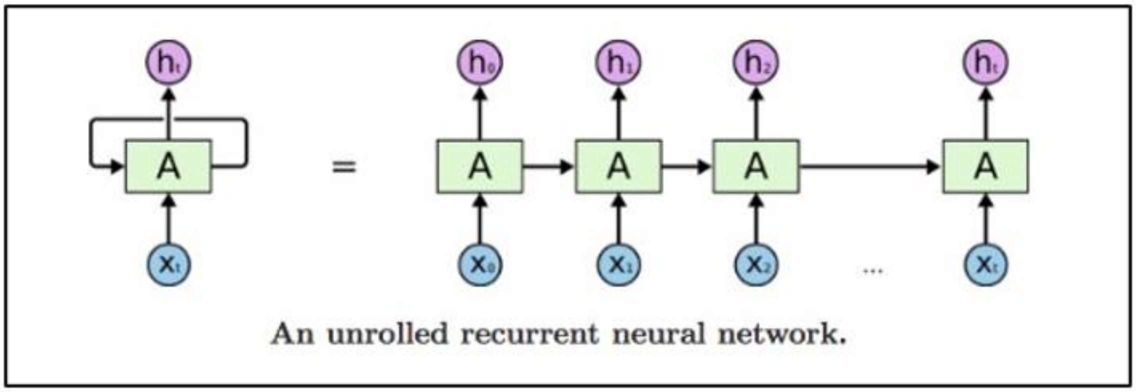

Figure 2: An unrolled Recurrent Neural Network Model [45]

Where σ represents the sigmoid activation function, typically logistic in nature. This function introduces a non-linear transformation, taking a real-valued input and mapping it to an output within the range of 0 to 1. The matrices Whx and Whh are associated with standard weights, linking the input and the hidden layer, as well as recurrent weights, linking the hidden layer to itself across successive time steps. The vectors bh and by serve as bias parameters, enabling each node to adjust by learning an offset.

The output vector $\hat{y}(t)$ predicts the subsequent value in the sequence. Considering the illustration in Fig 2, The RNN networks share weights across time steps, resembling both cyclic behaviour and a deep network. They can be trained over multiple time steps using "backpropagation through time" (BPTT) [46].

Long short-term memory (LSTM)

In 1997, Hoch Reiter and Schmid Huber introduced the concept of LSTM. which was developed as a solution to the problems associated with traditional RNNs, specifically addressing concerns related to exploding and vanishing gradients [47].

LSTMs, while similar to RNNs with hidden layers, use memory cells instead of standard nodes. These cells are interconnected and maintain a consistent weight, allowing gradients to flow across multiple time steps without vanishing or exploding issues.

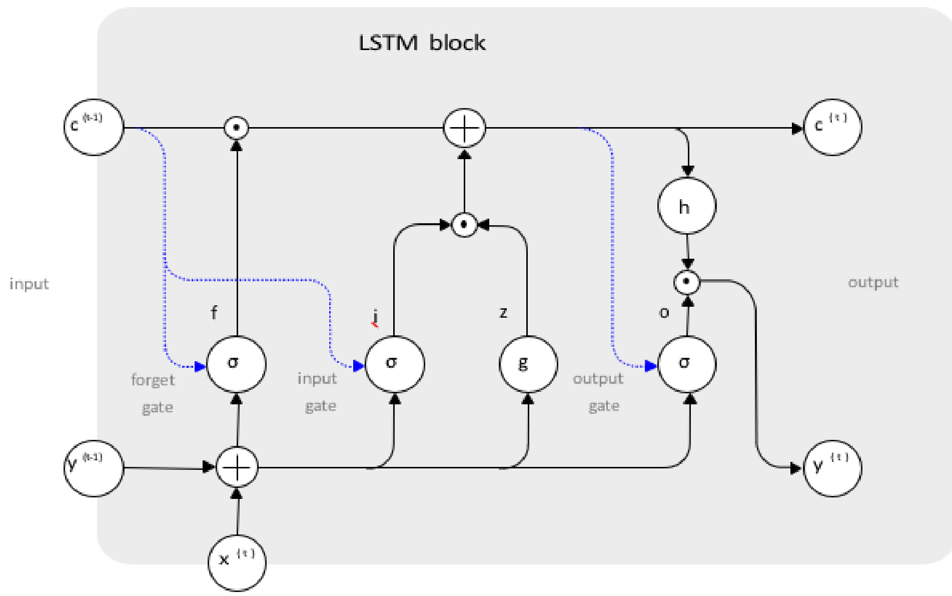

Fig 3: LSTM Cell showing the gates [48]

Fig 3 displays the architecture of a vanilla LSTM block, which involves the gates, the input signal $x^{(t)}$, the output $y^{(t)}$, the activation functions, and peephole connections. The output of the block is recurrently connected back to the block input and all of the gates.

The equations provided below pertain to three gates and the cell state [49]:

- Input Gate (i_t): The input gate decides the amount of information from the present input that should be preserved in the cell state.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad \ldots. (4)$$
$$\tilde{c}_t = \tan h(W_c[h_{t-1}, x_t] + b_c) \quad \ldots. (5)$$

- Forget Gate (f_t): The forget gate controls the amount of previous cell state information to be forgotten.

$$f_t = \sigma\left(w_f[h_{t-1}, x_t] + b_f\right) \qquad \ldots. (6)$$

- Output Gate (O_t): The output gate controls the quantity of information to be emitted according to the current cell state.

$$O_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \qquad \ldots. (7)$$

$$h_t = O_t \tan h(C_t) \qquad \ldots. (8)$$

Cell State (C_t): The cell state functions as the memory component within the LSTM network. It facilitates the transfer of information across the sequence and maintains long-term relationships. The cell state can undergo updates, be retained or be disregarded, all depending on the gating mechanisms in place.

$$C_t = f_t C_{t-1} + x_t \tilde{C}_t \qquad \text{…. (9)}$$

Where C_{t-1} corresponds to previous cell state.

Symbols and functions:

$W_i, W_c, W_i, W_c, W_f, W_o$ are weight matrices for input, candidate, forget and output gate

b_i , b_c, b_i , b_c , b_f , b_o stands bias vectors for input, candidate, forget and output gate

h_{t-1} indicates the previous hidden state

x_t signifies the current input

σ corresponds to sigmoid function, and

tanh represents hyperbolic tangent function.

Gated Recurrent Unit (GRU)

GRUs (Gated Recurrent Units) were introduced as an alternative to LSTMs to reduce computational demands, and this concept was originally introduced by Cho *et al*. in the year 2014 [50]. GRUs function as a gating mechanism in recurrent neural networks. They resemble LSTMs but are more parameter-efficient by omitting an output gate. This streamlined structure allows GRUs to be trained faster than LSTMs. GRU created with the purpose of capturing extended dependencies within sequential data [51].

The update gate and reset gate in GRU are defined as follows:

Update gate:

$$z_t = \sigma(x_t U^z + h_{t-1} w^z) \qquad \text{…. (10)}$$

Reset gate:

$$r_t = \sigma(x_t U^r + h_{t-1} w^r) \qquad \text{…. (11)}$$

Where σ logistic denotes the sigmoid function, x_t and h_{t-1} represents input and previous hidden state respectively, U^z, w^z, U^r and w^r are corresponds to the weight matrices which are learned.

The update gate decides the quantity of information to be refreshed and conveyed to the current time step (t), whereas the reset gate manages the aspects of the previous hidden state (h_{t-1}) that should be discarded or neglected.

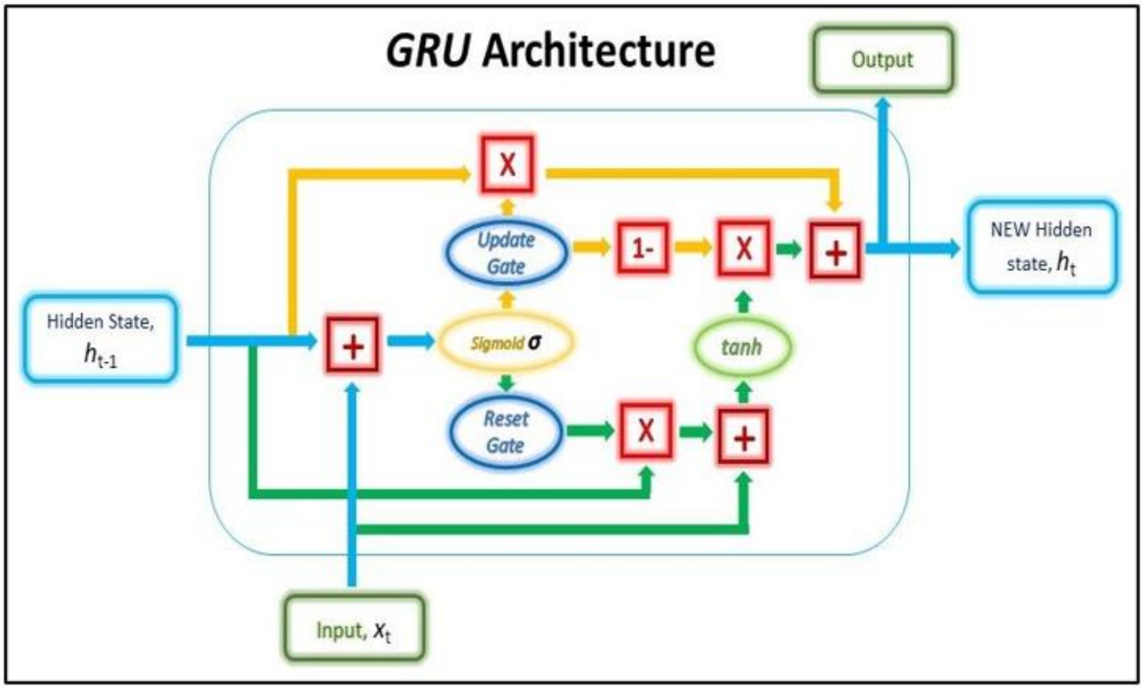

Fig 4: GRU Block diagram [51]

Fig 4 indicates x_t is an input state, h_t represents a new hidden state, O is an output state, h_{t-1} signifies previous hidden state, σ corresponds to the sigmoid function and tanh is the hyperbolic tangent function.

The candidate activation in GRU is computed as:

Candidate activation:

$$h_t = tanh(x_t U^h + (h_{t-1} r) w^h \qquad \ldots. (12)$$

Where U^h and w^h represents the weight matrices which are learned, x_t and h_{t-1} denotes input and previous hidden state respectively, r is reset gate, $tanh$ is hyperbolic tangent function.

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The candidate activation signifies potential new data that may be incorporated into the hidden state (h_t). This is achieved by merging the previous hidden state, which is adjusted by the reset gate, with the current input (x_t).

The hidden state in GRU is updated using the update gate:

Hidden state update:

$$s_t = (1 - z)h_t + zh_{t-1} \qquad \text{.... (13)}$$

Where h_{t-1} represents previous hidden state, h_t denotes Candidate activation state, z is update gate.

The update gate manages the balance between the prior hidden state and the candidate activation, thus dictating the impact of each on the present hidden state ($\boldsymbol{h_t}$).

Stacked LSTM

Due to rapid progress in computer hardware and the widespread adoption of diverse deep learning algorithms, deep architectures have demonstrated their remarkable capacity to independently extract features. Consequently, incorporating multiple LSTM layers into a deep neural network based on LSTM holds significant significance. The fundamental idea behind deep neural networks revolves around employing multiple layers for nonlinear mapping, facilitating the hierarchical extraction of features from input to output. This visualized concept is illustrated in Fig 5, where the output from the hidden layer not only advances over time but is also used as input for the subsequent LSTM hidden layer [52].

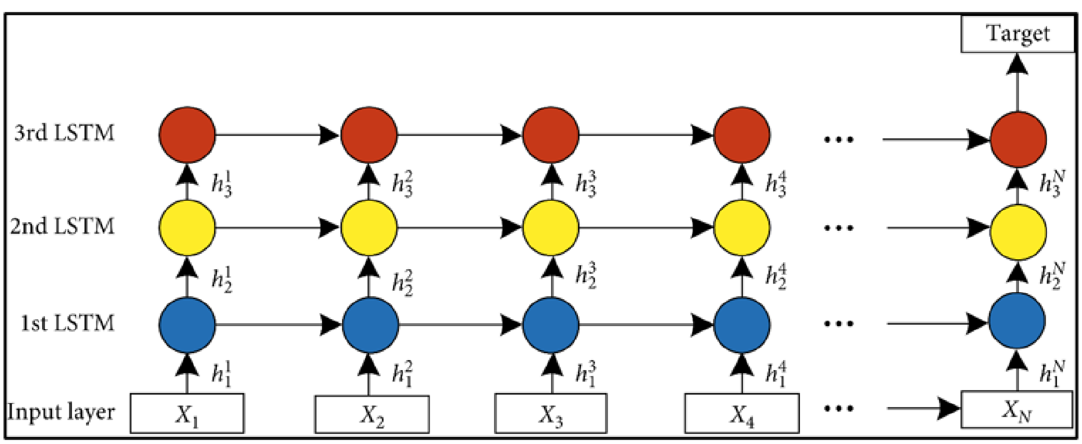

Fig 5: Stacked LSTM [53]

Evaluation of Forecasting Techniques:

Forecasting techniques will be evaluated using standard criterion of evaluation. Following are some measures for comparison:

The **Mean Absolute Percentage Error (MAPE)** is another commonly used measure. It is the sum of the individual absolute errors divided by the demand (each period separately). It is the average of the percentage errors.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{(F_t - A_t)}{A_t}\right| \times 100 \qquad \text{.... (15)}$$

Where F_t is a forecasted value for time t and A_t is the actual value for time t, n is the total number of forecasts.

The **Root Mean Squared Error (RMSE)** is one of the most commonly used measure of forecast accuracy. It is defined as the square root of the average squared error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2} \qquad \text{.... (16)}$$

Where F_t is a forecasted value for time t and A_t is the actual value for time t.

The **Symmetric Mean Absolute Percentage Error (SMAPE)** is a percentage error measure that gives equal weight to positive and negative errors

$$SMPE = \frac{1}{n}\sum_{t=1}^{n}\frac{(|A_t - F_t|)}{\left(\frac{A_t + F_t}{2}\right) \times 100} \qquad \text{.... (17)}$$

Where F_t is a forecasted value for time t and A_t is the actual value for time t, n is the total number of forecasts.

RESULT AND DISCUSSION

Dataset

In this research, we have utilized secondary data sourced from AGMARKNET (https://agmarknet.gov.in/) which pertains to cotton prices in the Rajkot district market of Gujarat, India. Rajkot Market was chosen as the representative market because it has the highest level of cotton arrivals. The dataset covers the period from April, 2002 to April, 2023 and comprises 7696 observations. However, it's important to note that the dataset has its limitations, including missing

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observations of 789 out of 7696, which were addressed by filling in the gaps with the average values from the preceding five working days.

Data description

We conducted a statistical analysis of cotton prices dataset which we have collected. The dataset's mean cotton price is Rs. 4326.50 per quintal. The 1st quartile is Rs. 2660 per quintal, the 3rd quartile is Rs. 5250 per quintal and the median stands at 4253 per quintal. These statistics indicate that the data's distribution is non-normal due to the disparity between the mean and median. The cotton prices exhibit a substantial degree of variation, ranging from a minimum of Rs. 1650 per quintal to a maximum of Rs. 12370 per quintal. Furthermore, the data is positively skewed with a skewness value of 1.21, as shown in the Table 1.

Table 1: Description of Cotton price data from 2002 to 2023 of Rajkot market

Parameter	Indian Rupees per quintal (₹/q)
Number of observations	7696
Average	4326.50
Standard deviation	1983.78
Minimum value	1650
1st quartile	2660
Median	4253
3rd quartile	5250
Maximum value	12370
Skewness	1.21
Kurtosis	1.93

Fig. 6 shows the fluctuations of cotton prices in Rajkot market of Gujarat from 2002 to 2023. Over this 21-year span, the prices exhibit substantial fluctuations, reflecting the intricate dynamics of the cotton market. These fluctuations are influenced by factors like global economic conditions, climatic events and government policies. Notably, the prices hit a peak in certain years, such as 2011 and experienced troughs in others.

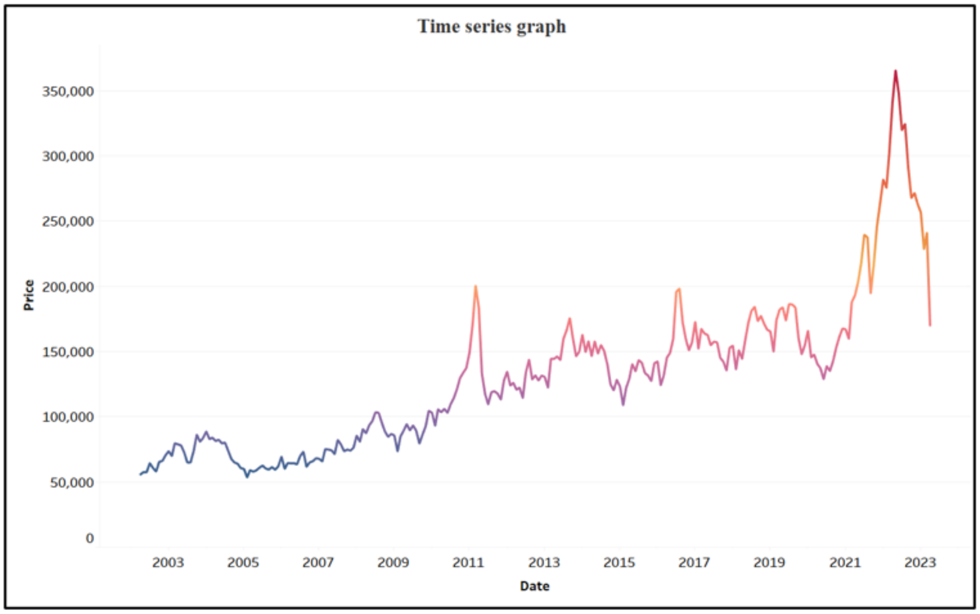

Fig 6: Time series graph of cotton price data

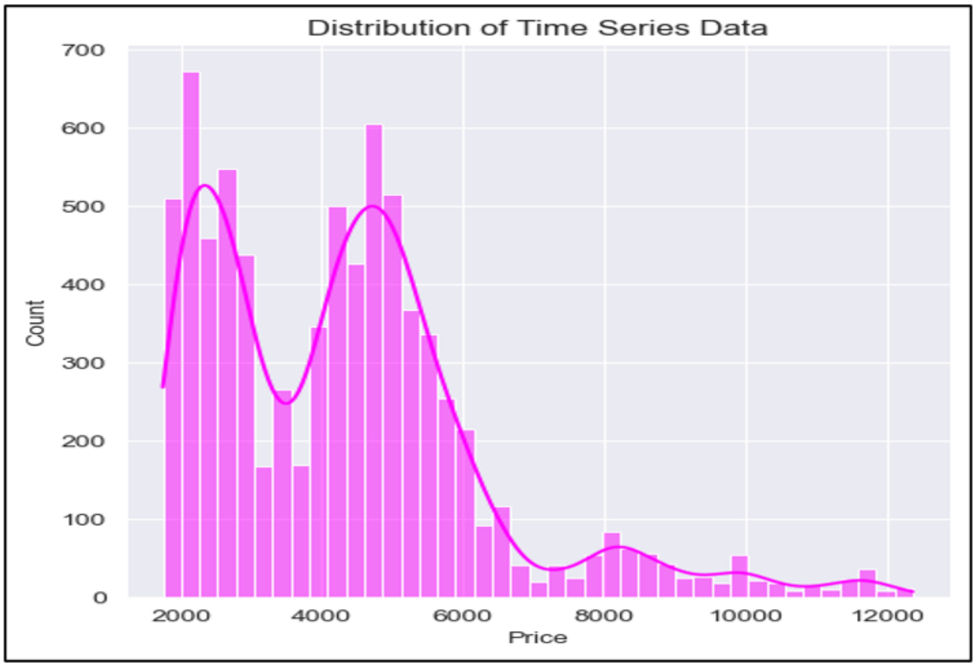

Fig 7: Time series distribution of cotton price data

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The distribution curve, accompanied by a histogram in Fig. 7, paints a revealing picture of the cotton price data's statistical characteristics. The positively skewed nature of the distribution is clearly evident. This skewness, with a value of 1.21, indicates that the data's tail extends toward higher prices, reflecting occasional price spikes. The majority of data points cluster around the median value of Rs. 4253/quintal. However, this central tendency is influenced by a handful of outliers on the higher end of the price range.

Model building

To assess the effective cotton price prediction algorithm for Gujarat in 2023, we utilized daily modal price data from the Agmarknet website [57], covering the period from 2002 to 2023. Table 2 outlines the division of the data into training and testing sets, along with the specific period for forecasting cotton prices. We adopted a 90% training and 10% testing data split, this modification was made to ensure a more robust training phase, allowing the model to capture intricate patterns and relationships within the data, mitigate overfitting concerns and accommodate the learning of diverse data patterns and potential noise or outliers. Moreover, when working with large datasets, dedicating the majority of the data to training ensures sufficient learning opportunities. To gauge the model's performance, we initially constructed it using the training data and then evaluated it using the testing data by comparing the model's predictions to the actual observed values.

Table 2: Details of splitting price data

Crop	Year	Total data points	Training data points	Testing data points
Cotton	2002 to 2023 (21 years)	7692	6922 (90 percent)	770 (10 percent)
Forecasting period		May 2023 to April 2024		

Various forecasting models including ANN, RNN, LSTM, GRU and stacked LSTM, as detailed in the methodology section, were trained using the designated training dataset. Subsequently, the testing dataset was employed to identify the optimal model. Table 3 provides the accuracy metrics for the models under evaluation. The model selected exhibited the most favourable performance, characterized by the lowest values across accuracy metrics such as RMSE, MAPE, SMAPE and MAE when applied to the testing dataset. This chosen model was then utilized for predicting prices over the upcoming 365 days, spanning from May 2023 to April 2024.

Table 3: Accuracy comparison of forecasted cotton price by different models on test dataset

MODELS	RMSE	MAPE	SMAPE	MAE
STACKED_LSTM	0.897	0.456	0.579	31.038
LSTM	4.735	0.498	0.590	34.092
GRU	14.48	0.737	0.870	41.834
RNN	35.96	0.9807	1.044	54.409
ANN	177.09	1.406	1.31	76.864

The Area chart in Fig 8 illustrates the Root Mean Squared Error (RMSE) values associated with different forecasting models on testing dataset. Each model is represented by a distinct area size directly corresponding to the magnitude of RMSE. Notably, the Stacked LSTM model stands out with the smallest area, indicating the lowest RMSE of 0.897 among all models. This smaller area denotes superior predictive accuracy, suggesting minimal deviation between the Stacked LSTM's forecasted prices and the actual observed prices. In contrast, larger areas representing LSTM, GRU, RNN and ANN models indicate higher RMSE values, highlighting increased predictive errors in their respective forecasts. as confirmed by the results in Table 3.

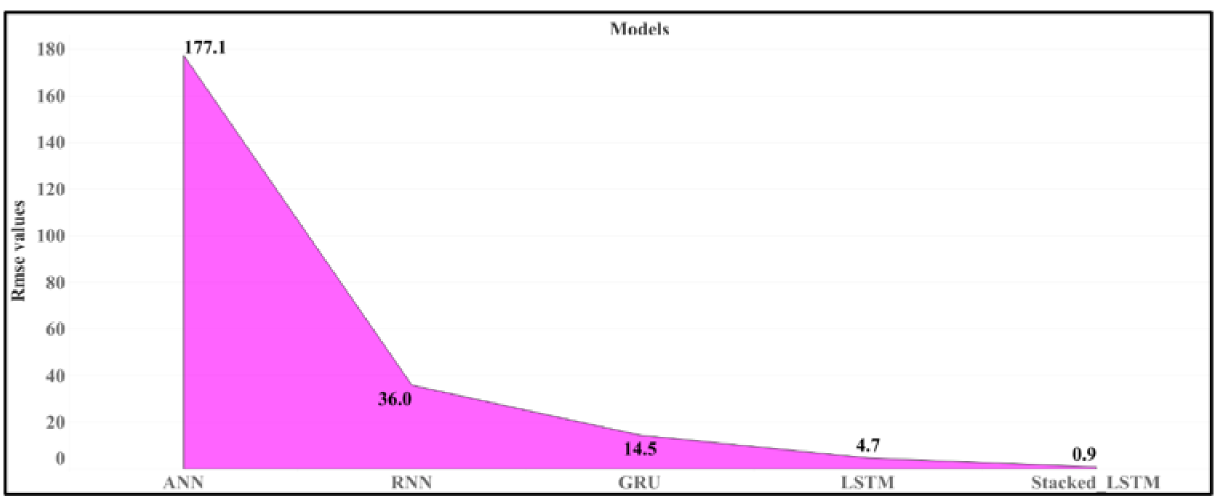

Fig 8: Area chart presenting RMSE values of models on test dataset

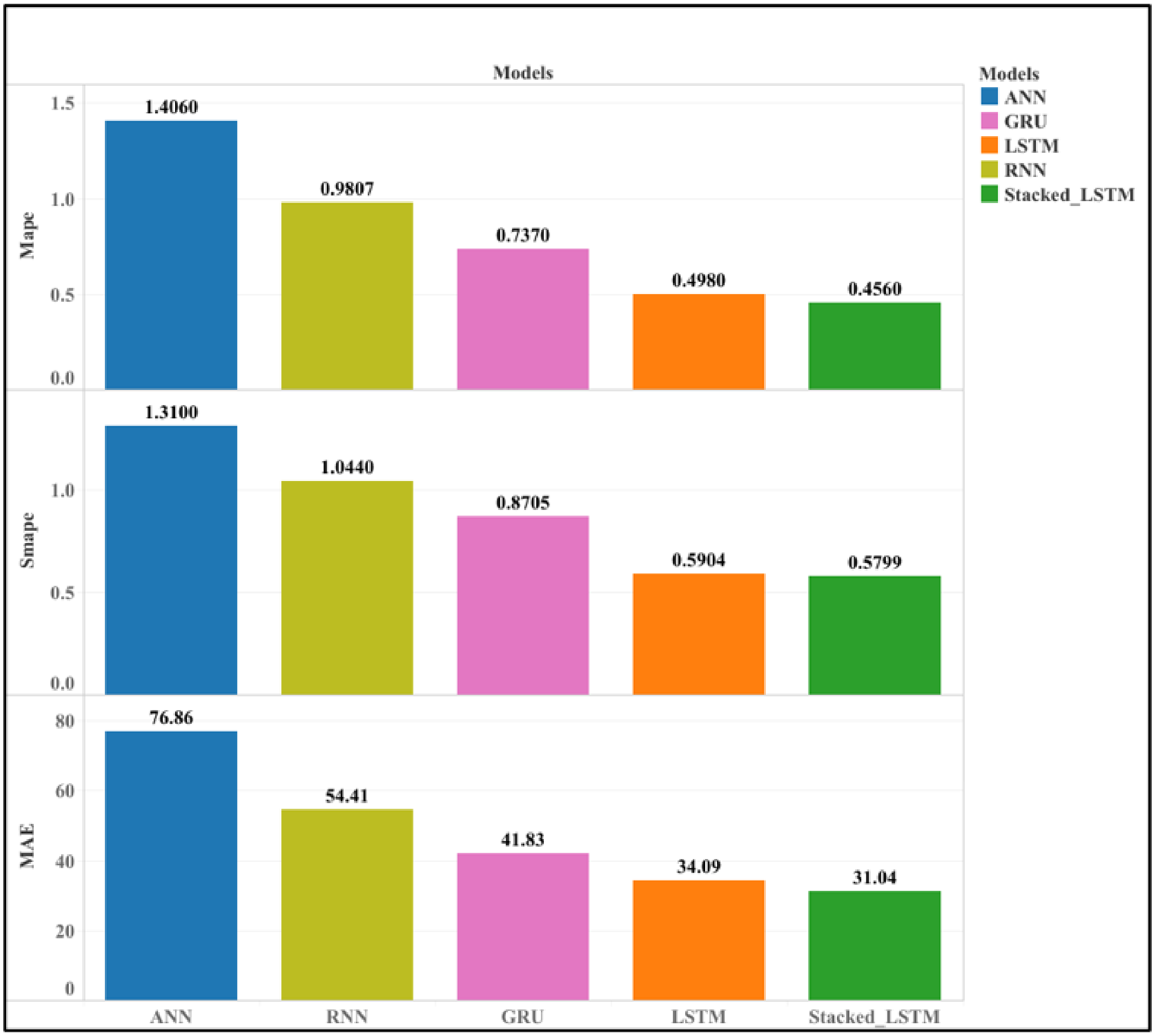

Fig 9: Bar chart presenting Accuracy measures of models on test dataset

Bar chart presented in Fig 9 visualize the performance comparison of MAPE, SMAP and MAE values across different models on testing dataset, making it simple to understand the results. The Stacked LSTM model showed the best performance, indicating smaller errors compared to other models. It had lower values for MAPE (0.456), SMAPE (0.579) and MAE (31.038). In contrast, methods like LSTM, GRU, RNN and ANN resulted in larger values for these error metrics, indicating they were less accurate in predicting future prices. This suggests that the Stacked LSTM method performed better in making more accurate estimates for future prices.

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Tuning Parameters of stacked LSTM model

In this segment, we elaborate on the parameters and hyperparameters employed in the Stacked LSTM model. The architecture and parameter details of the optimal Stacked LSTM model are summarized in Table 4.

Table 4: Tuning parameters of Stacked LSTM

Parameters	
number of inputs	30
time step	30
features	1
number of LSTM	3
Neurons in layers	
Hidden 1st layer	7
Hidden 2nd layer	8
Hidden 3rd layer	12
Output layer	1
Other hyperparameters	
Learning Rate	0.0001
Epochs	30
Batch size	32
Optimiser	Adaptive Moment Estimation

The proposed design of the Stacked LSTM model, outlined in Table 4, encompasses a stratified arrangement involving the sequential stacking of three LSTM layers. These hidden layers are structured with 7, 8, and 12 neurons, respectively, progressively escalating in capacity. The input layer is configured to handle 30 input values, representing historical time-series data of cotton prices, the output layer comprises a single neuron responsible for generating forecasted price outputs. Additionally, the model is fine-tuned with various essential hyperparameters, including a training duration of 30 epochs, a moderate batch size of 32 for iterative optimization, a learning rate set at 0.0001 and the utilization of the Adam optimizer to enhance predictive accuracy and capture intricate temporal dependencies within the data.

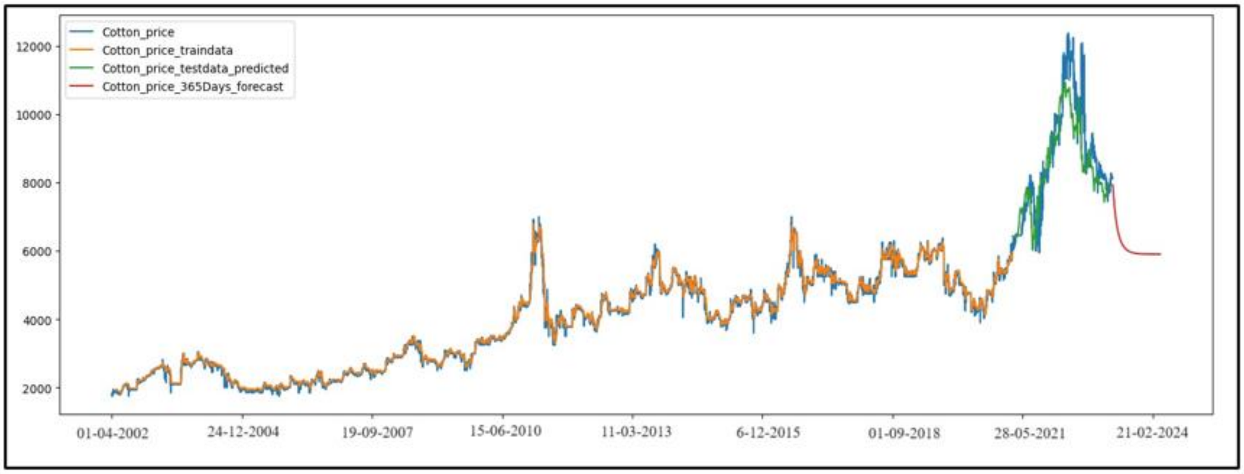

Fig. 10: Stacked LSTM Model: Training, Testing and Prediction Performance graph

Fig 10 demonstrates the performance of the Stacked LSTM model on both the training dataset comprising of 6922 observations and the predicted testing data of 770 observations. Among all the models considered in this study, the Stacked LSTM emerges as the foremost forecasting model for cotton in 2023, as evident from Table 3. Employing this model, the forecast of cotton prices for the next 365 days, spanning from April 22nd, 2023, to April 19th, 2024, is presented in Fig 10. The graph depicts the projected cotton prices for the forthcoming 365 days, showing a consistent decrease in price until reaching 5000 rupees per quintal and maintaining this level throughout the year 2024.

DISCUSSION

The evaluation results in Table 3 show that the Stacked LSTM model exhibited the highest level of predictive accuracy among all models, establishing it as a dependable option for future forecasting tasks. It displayed outstanding performance with the lowest combination of RMSE of 0.897, MAPE of 0.456, SMAPE of 0.579 and MAE of 31.038 when assessed with the test data from the time series dataset. In the overall ranking, the Simple LSTM model closely followed as the second-best performer, with the GRU, RNN and ANN models following in sequence.

This research also highlighted a consistent trend in cotton pricing, noting a regular peak occurring every March. Specifically, the Stacked LSTM model showed its highest forecasting error of 2

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percent during the harvesting months of March and April 2023, while recording a somewhat higher forecasting error of 3.31 percent in the pre-sowing months of October and November 2022. These findings carry significance for farmers as they can strategically plan their production to coincide with periods of increased prices. Additionally, traders and policymakers can leverage this valuable information to make more profitable decisions and craft effective policies based on these price patterns. These outcomes align with prior studies that also recognized the dominance of the Stacked LSTM model in diverse areas, including Stock market forecast [54], Wind speed forecasting [55], dynamic spot price forecasting [56], Stock market behaviour prediction [58], Predicting the number of customer transactions [59], day-ahead electricity price forecasting [60] and predicting the number of cases and deaths caused by COVID-19 [61]. Additionally, studies have emphasized the significance of the number of LSTM layers used in stacked LSTM models as shown in [62].

CONCLUSION

Our comprehensive exploration of deep learning models demonstrates that the Stacked LSTM model outperforms other models in forecasting cotton prices in Gujarat from May 2023 and April 2024. It consistently displays an annual peak in March and excels by showcasing minimal forecasting errors, with only a 2% error during the harvest period (March and April 2023), compared to 3.31% during the pre-sowing months (October and November 2022). The model's exceptional performance across diverse evaluation metrics attests to its ability to recognize prolonged data patterns, establishing it as the favoured option for precise cotton price forecasting. These findings hold significant implications for stakeholders in the cotton industry, offering them valuable insights to inform strategic decisions related to production and marketing strategies, assists farmers in adjusting to market changes and promotes investments.

This study faced inherent challenges in addressed missing values, which is incorporated by imputing the average price from the preceding five working days. Future endeavours should address the challenges related to vanishing and exploding gradients while further refining data pre-processing techniques. Looking ahead, incorporating weather patterns and arrival data could enhance predictions by considering how climate and market arrivals impact prices. Furthermore, exploration into hybrid models and ensemble techniques might offer a promising direction for even more accurate predictions in cotton price forecasting. In conclusion, this research contributes valuable insights into the potential of deep learning models for cotton price forecasting, emphasizing adaptability, accuracy and the Stacked LSTM model's efficacy as it emerges as the optimal choice for forecasting cotton prices in Gujarat, signifying its practical applicability and robust performance.

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