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Modeling and Forecasting of Producer Price Index (PPI) of Cheese Manufacturing Industries

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Abstract: Modeling and forecasting of complex time series data has grown as an attractive field thanks to machine learning. The PPI (Producer Price Index) of cheese manufacturing businesses was examined in this study utilizing a machine learning technique. Training and testing data sets were created for the goal of creating and validating a model. After that, we built deep learning models such as LSTM, BILSTM, and GRU and tested them on a training data set using metrics such as ME, RMSE, MAE, MPE, MAPE, and ACF1. These deep learning models were compared on the basis of RMSE for the testing data set. On this set of data, the LSTM model outperforms the BILSTM and GRU models in terms of machine learning performance. These three models' forecasting abilities are nearly identical. Policymakers and academics may find this study useful in building a body of knowledge about PPI in the cheese manufacturing industry. As a result, we feel that this work can be used as a textbook on how to apply machine learning techniques to complex time series.

Keywords: Producer Price Index (PPI); LSTM ;BILSTM; Forecasting.

1. Introduction

Cheese is a dairy product derived from the coagulation of casein, a milk protein derived mostly from cow, buffalo, goat, or sheep milk. It is available in a wide range of flavors, textures, and shapes. For millennia, cheese has been prized for its mobility and extended

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shelf life. Aside from that, it's a good source of minerals like calcium, which is vital for healthy bones, and high-quality proteins, which are necessary for muscle growth. The origin of the milk has a large influence on the texture and flavor of cheese [Fox,2017]. Fast food restaurants are among the world's largest consumers of cheese, and the fast food business is expanding at a healthy rate as the world's population and disposable incomes rise. Cheese consumption is likely to increase in the near future due to the rapid development of the fast food business (Gandhi & Zhou.2014). Emerging economies such as China and India are expected to boost the global cheese market in the coming years. Until recently, cheese consumption was mostly limited to Western countries. Cheese consumption in these markets is expected to climb due to the growing trend of westernization of food consumption patterns, as well as a booming economy, a growing middle-class population, and expanding urbanisation. The global cheese industry is benefiting from the rise of the organized retail sector. Many multinational corporations were previously unwilling to offer their products in growing markets because to concerns about spoilage, a lack of infrastructure and storage facilities, and a lack of information about the expanding market. Despite this, many businesses are investing in India and China, where the number of organized retail stores is increasing (Gandhi & Zhou.2014).

As a result of increased marketing efforts by numerous players through various advertising media such as newspapers, television, etc., product awareness is rising among the general public in new markets. The global milk supply has been surpassed by the global dairy demand. This trend is expected to persist, even intensifying. Among the fastest growing dairy product categories in emerging countries are milk and yogurt [Roy, 2019]. The global cheese market developed fast in the 1990s and early 2000s, but has slowed since 2005, despite sustained development. The report's main point is that cheese has a bright future [Wiley, 2014]. However, the cheese segment must adapt to the new reality of crowded markets in the OECD and no cheese consuming tradition in many emerging dairy countries. The last five years have shown volatility [Roy, 2019]. From 2005 to 2008, dairy prices, particularly cheese, surged due to global economic boom. For the first time in three decades, global dairy demand outpaced supply. Due to the global financial crisis that began in mid-2008, prices fell and the global dairy sector was severely hit. From 2005 to 2008, global economic growth drove up the price of dairy products, particularly cheese. As a result, worldwide dairy demand surpassed supply for the first time in 30 years. As of mid-2008, the global financial crisis had wreaked havoc on the worldwide dairy business [Dobson & Christ, 2000]. Mishra et al. (2020 & 2021) and Yonur et al. (2021) employed time series models to forecast pulses, sugarcane, and wheat.

2. Methodology

Recurrent Neural Network (RNN) Model: The RNN model is a sort of neural network in which the previous step output produced is fed into the current step input, creating a loop. However, in certain scenarios, such as when predicting the next word of a sentence, we require the previous word and there is an urgent need to recall these previous words; as a result, using the Recurrent Neural Network model with hidden layer is more effective in resolving this issue than using the traditional neural network. The Hidden state is the primary and most significant RNN feature, as it is responsible for remembering certain information about a sequence. It is also the most difficult to implement. The memory is a component of the RNN that retains all information about the calculations that have been performed. Because it performs a same work on all of the hidden layers or inputs to produce the outputs, the RNN memory employs the same parameter for each of the different inputs. Therefore, as compared to other neural networks, the complexity of parameters is considerably reduced.

Long Short-Term Memory (LSTM) Model: In sequence prediction issues, the Least Squares Time Series Model (LSTM) is a sort of recurrent neural network capable of learning order dependence. When it comes to the past, the LSTM model has had a significant impact; it has the ability to learn from sequential data, which means that it has a long-range dependency, which makes it more accurate when compared to ordinary RNNs. The error backflow problem is caused by the back-propagation method in the RNN architecture. The back-propagation method is based on the composite function chain rule, which is the core concept underlying it. When searching for the local minimum of a loss function, Stochastic Gradient Descent (SGD) is the most efficient and fastest approach to employ. Once the gradients of the existing nodes of the computational graph have been obtained internally, we can retrieve the gradients of the nodes that have a start point by calculating the start point gradient and then looking in the direction of a negative gradient, as shown in Figure 1. It is the memory cell that is the fundamental structure of the LSTM. It makes use of cell states to remember information about temporal contexts and to transmit unit outputs directly in distinct time steps over time. The forget gate, input gate, and output gate are all components of the LSTM memory cell, and they are all responsible for managing the flow of information between distinct time steps. Background radiation was forecasted using time-series rainfall data using neural networks based on the LSTM algorithm, as demonstrated in this study. The problem of vanishing gradient refers to the mathematical challenge of understanding the long-term relationships in the structure of recurrent neural networks while using a recurrent neural network. As the length of the sequence increases, it becomes more difficult to capture the influence in the earliest phases of the sequence. The gradients to the first few input points diminish and become equal to zero as the number of input points increases. The actual architecture of LSTM proposed is implemented with the sigmoid function for forget gate and input gate and with the tanh function for candidate vector that updates the cell state vector. These activation functions of LSTM are calculated for Input gate (I_t) , Output gate (O_t) , Forget gate (F_t) , Candidate vector (C'_t) , Cell state (C_t) , and Hidden state (h_t), using the following formulae:

$$I_t = \text{sigmoid}(Wi\ [X(t),\ h_t{-}1\ ] + b_i)\ \text{(Input Gate)} \tag{1}$$

$$F_t = \text{sigmoid}(Wf\,[h_t - 1, X(t)\,] + b_f\,)\ \text{(Forget gate)} \tag{2}$$

$$O_t = \text{sigmoid}((Wo[h_t - 1, X(t)] + b_o)\ \text{(Output gate)} \tag{3}$$

$$C'_t = \tanh(Wc[h_t - 1, X(t)]+b_c)\ \text{(Candidate vector)} \tag{4}$$

$$C_t = F_t - C'_t - 1 + I_t - C'_t\ \text{(Cell State)} \tag{5}$$

where X(t) is the input vector, h_t–1 is the previous state hidden vector, W is the weight and b are the bias for each gate. The implementation of encoder in this model will be contained in the last hidden statement of the LSTM.

where X(t) is the input vector, $h_{t''1}$ is the previous state hidden vector, W is the weight, and b is the bias for each gate. The basic structural representation of the LSTM network is shown in Figure 1.

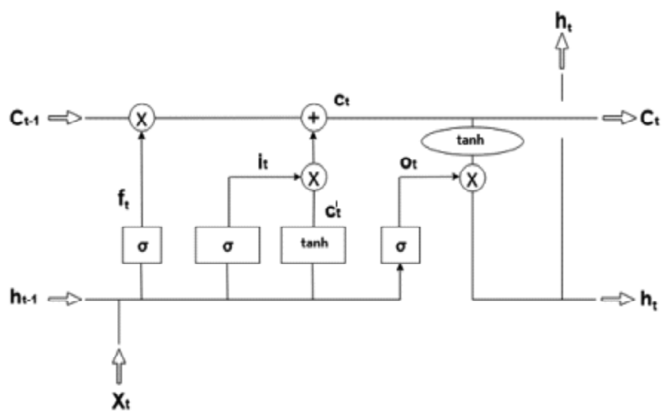

Figure 1

The implementation of encoder in this model will be contained in the last hidden statement of the LSTM.

Bidirectional Long Short-Term (BiLSTM) Model: Long Short-Term Model (LSTM) and Bidirectional Recurrent Neural Network (BiRNN) are combined to form the BiLSTM model, which combines the advantages of both models (LSTM). BiLSTM is a model that propagates the inputs in both the forward and reverse directions, as the name implies. The BiLSTM model is a two-way network that can be used to store both future and past data simultaneously. The BiLSTM model is one of many parallel calculations that have been performed. With two LSTMs, the first step is to encode the word “wp,” and then the word “wq.” This procedure is referred to as Bidirectional LSTM (BiLSTM).

$$h^{(q)} = \text{BiLTSM}\ (w^{(q)};\ \theta^{(q)})\ \&h^{(p)} = \text{BiLTSM}\ (w^{(p)};\ \theta^{(p)}) \tag{6\&7}$$

Gated Recurrent Unit (GRU) Model: The GRU model uses both update-gate and reset-gate to tackle the vanishing gradient problem of standard RNN. The update-gate and reset-gate determine the information sent to the output. The ability to teach these vectors to store information over time without losing it or eliminating it makes them distinctive. Over time, GRUs have proven to perform better on less frequent datasets.

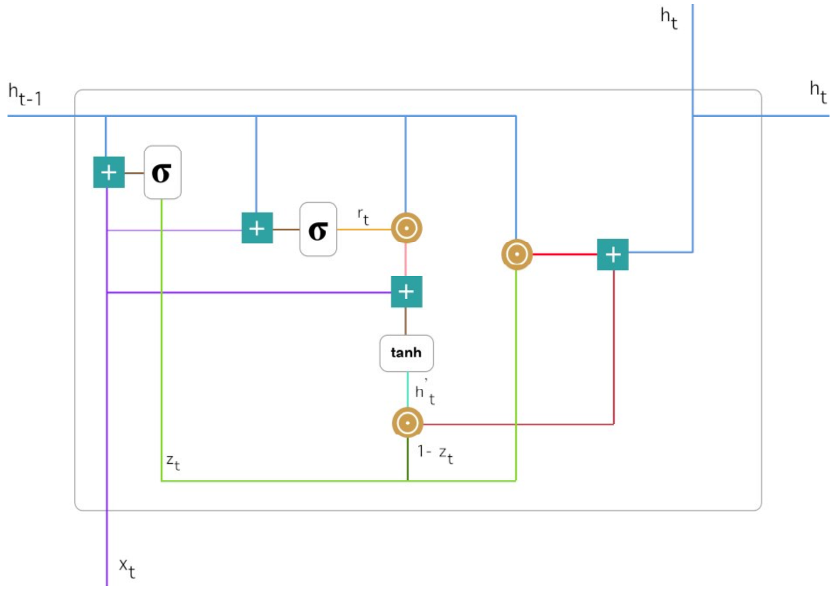

Figure 2

All the above RNN methods, including descriptive statistics, are applied to the data set of the average monthly producer price index (PPI) of cheese manufacturing industries. Industry Producer Price Index Cheese Manufacturing, Index, Jun 1981 = 100, Monthly, Not Seasonally Adjusted. December 1972 to June 2021 monthly data and using 80% of the dataset for training to learn deep learning models and 20% for testing deep learning models (price in dollars).

4. Results and Discussion

Throughout the research, the Producer Price Index (PPI) of the cheese manufacturing businesses is examined and forecasted over a period of time. A program called the Producer Price Index (PPI) calculates the average change in selling prices for domestic producers' output over a given period of time. The prices included in the PPI for many commodities and services are derived from the first commercial contacts, which means that they are historically accurate. The ability to predict pricing is critical for developing marketing strategies that are advantageous to domestic producers and suppliers (Schmit and Kaiser 2006). Cheese demand has been increasing steadily in recent years, which can be attributed to a shift in consumer consumption patterns.A study by IMARC Group predicts that the cheese market in India to grow at CAGR of 24.80% during 2021-2026 (*https://www.imarcgroup.com/cheese-market-in-india*). As a result of this focus on the market, we will be looking at how producer prices fluctuate. 80 percent of the dataset from December 1972 to June 2021 monthly data is used for training and 20 percent of the dataset is tested (price in dollar). Figure 1 depicts a conceptual framework for the steps involved in the analysis of data for a deep learning model.

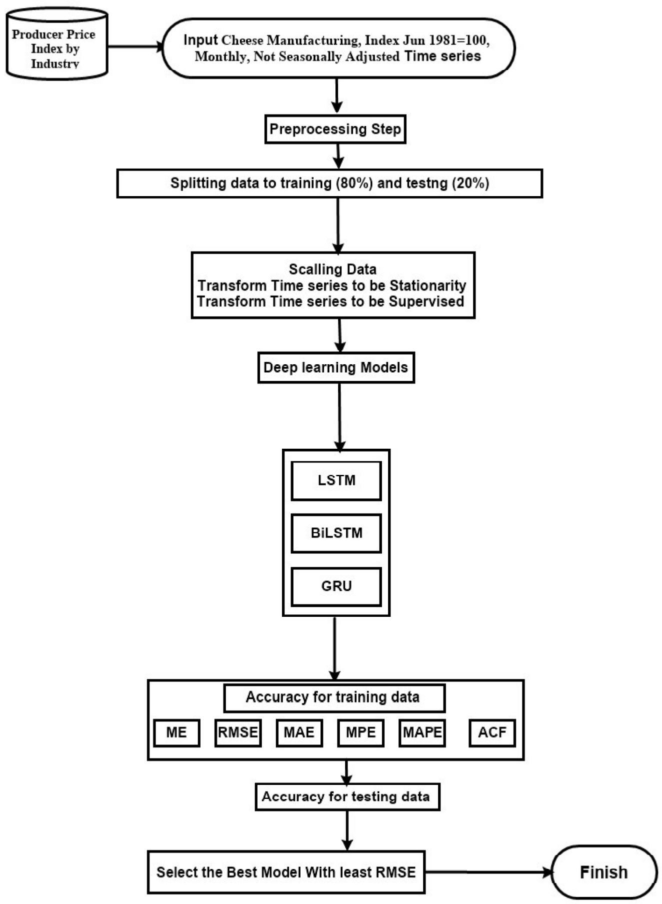

Figure 3: Conceptual framework for steps involved in analysis of data for deep learning

In Table 1, the descriptive statistics of PPI of the cheese manufacturing industry is presented.

Table 1: Descriptive statistics of the Producer Price Index by Industry

Producer Price Index by Industry:	*Mean*	*Minimum*	*Maximum*	*Standard Deviation*	*Skewness*	*Kurtosis*
Cheese Manufacturing, Index Jun 1981=100, Monthly, Not Seasonally Adjusted	126.2	46.3	226.5	0.3170162	0.3170162	2.2801

The table shows that the mean value of PPI was expected to be 126.2 from 1972 to 2021, with a maximum of 226.5 and a minimum of 46.3. The highest and minimum values represent the PPI range, with a standard deviation of 0.3170 calculated. Asymmetric and leptokurtic distributions are also suggested by the data set. Deep learning techniques were used after visualizing the data to analyze the data using previous PPI and anticipate real-time forecasting for the same. Based on the goodness of fit (Table 2) of the training data set, we compared three deep learning models: LSTM, BI-LSTM, and GRU.

Table 2: LSTM, BI-LSTM, and GRU Model fitted to Producer Price Index by Industry for training data

Model	*ME*	*RMSE*	*MAE*	*MPE*	*MAPE*	*ACF1*
LSTM	-1.695285	3.825701	2.80478	-1.773014	2.57623	0.05795
BILSTM	-5.426139	6.735198	6.002025	-5.192126	5.550897	0.339824
GRU	-3.529196	5.06814	4.26026	-3.696647	4.149989	0.233992

From the table, it can be noted that LSTM model was found to be having lowest RMSE, MAE, MAPE and ACF1. BILSTM model performed lowest ME, MPE values.Application of deep learning procedure has many advantages over the traditional forecasting techniques. The RMSE values for testing data in all the models are depicted in Table 3 (Devi *et al*., 2021).

Table 3: RMSE for testing data

Model	*RMSE*
LSTM	7.246806
BILSTM	5.6776
GRU	6.316514

From the table 3 it can be noted that lowest prediction errors was found in case of BILSTM model with 5.6776 followed by GRU having RMSE 6.3165 and LSTM having error as 7.2468.The figures depicting the graph of data set, training prediction and testing prediction for LSTM, BILSTM and GRU are presented in figure 1, 2 and 3, respectively. From the figure it can be noted that predictions of LSTM model outperforms the other models viz., BILSTM and GRU.

Table 4 depicts the forecasting of PPI in Cheese manufacturing industry by LSTM, BI-LSTM and GRU models. The table depicts that after September, 2021 there will be consistent decrease in forecasted PPI according to all the models. It is considered as an objective for adjusting prices in long term.

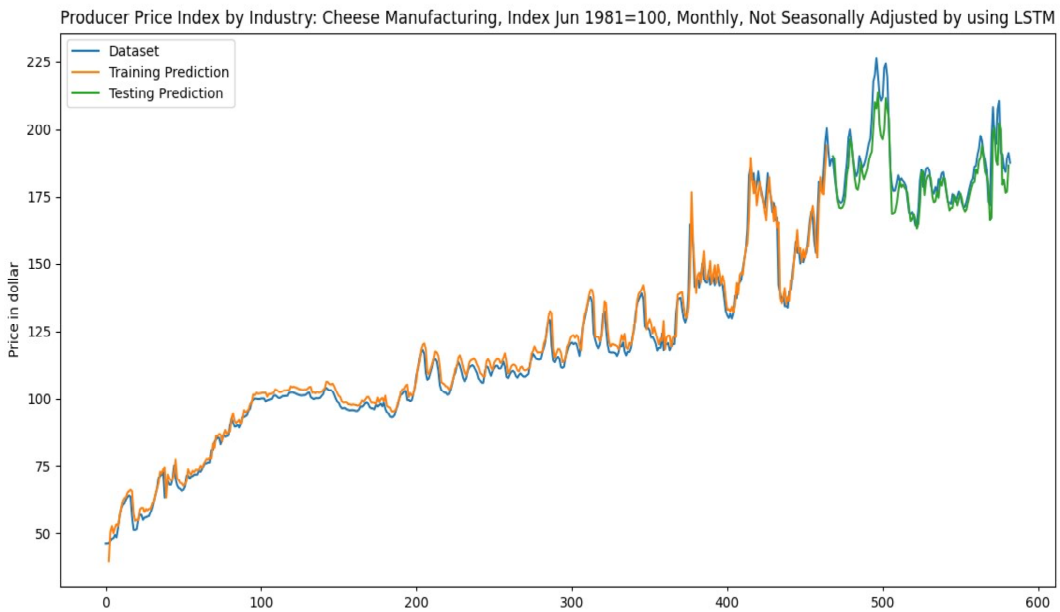

Figure 1: PPI prediction using LSTM

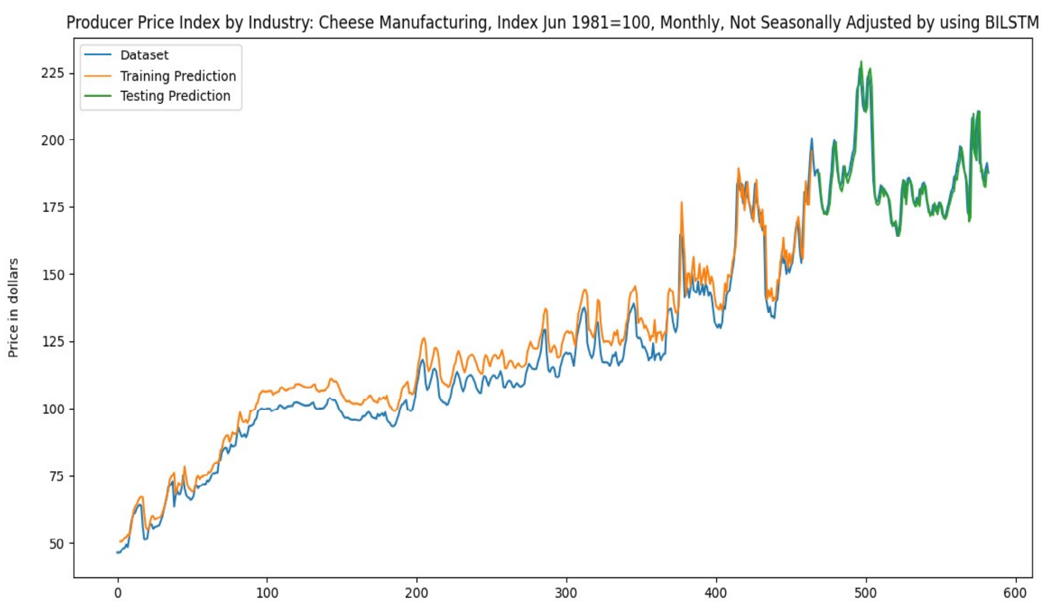

Figure 2: PPI prediction using BILSTM

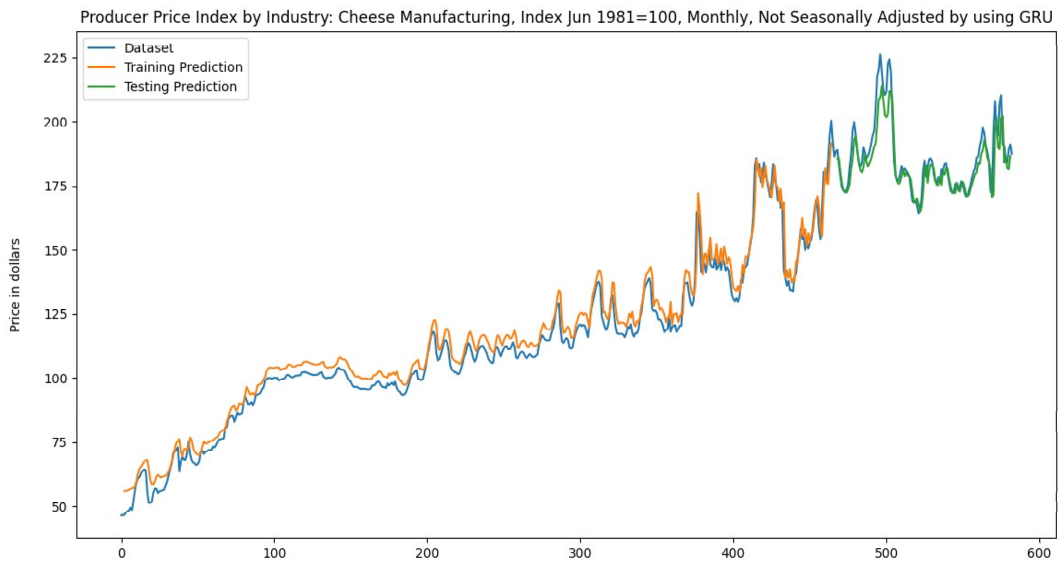

Figure 3: PPI prediction using GRU

Table 4: Forecasting from 2021-07-01 to 2022-12-01 for Producer Price Index by Industry

Date	*Producer Price Index by Industry LSTM*	*Producer Price Index by Industry BI-LSTM*	*Producer Price Index by Industry GRU*
2021-07-01	179.845764	185.040085	183.745911
2021-08-01	171.342667	182.908997	180.817169
2021-09-01	165.739014	180.952820	178.675919
2021-10-01	160.508789	179.162888	177.140259
2021-11-01	157.109924	177.557983	176.044601
2021-12-01	155.238129	176.155319	175.263260
2022-01-01	153.592682	174.962433	174.705551
2022-02-01	154.474625	173.975555	174.306961
2022-03-01	155.631653	173.181000	174.021759
2022-04-01	156.899170	172.557816	173.817474
2022-05-01	159.540680	172.081024	173.671051
2022-06-01	161.534286	171.724625	173.566025
2022-07-01	163.411346	171.463913	173.490662
2022-08-01	165.580643	171.276917	173.436584
2022-09-01	166.988922	171.145187	173.397736
2022-10-01	168.294128	171.053894	173.369858
2022-11-01	169.273712	170.991547	173.349808
2022-12-01	169.721161	170.949509	173.335434

This declining trend of PPI continues till January, 2022 after which the PPI increases. The increasing trend was seen in LSTM model while in BI-LSTM, the PPI declined again. In GRU model, there was marginal increase and decrease in PPI. There was not much difference seen in PPI in all the three models.

5. Conclusion

The cheese market in India is expected to develop significantly between 2015 and 2020. Cheese manufacturing industry producer pricing index (PPI) became a key factor in determining predicted behavior that is beneficial to India's economy.. A promising topic in the present is the development of forecasting models based on machine learning, particularly when dealing with complicated time series.. Our goal was to assess the goodness of fit of different models to training and testing data sets in order to arrive at this conclusion, and we did just that. When it comes to training data, the LSTM model is the best, whereas the BILSTM model is excellent for testing data. GRU models, on the other hand, did not perform as well as LSTM and BILSTM models. Nevertheless, these three models' projection patterns are remarkably similar from 2021-07-01 to 2020-12-01. The adaption of deep learning models to difficult time series data was effectively disclosed in this research. Additionally, we are optimistic that our research will have a positive impact on a wide range of policymakers, manufacturers, and researchers.

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