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Forecasting Hourly Energy Consumption Using LSTM: A Deep Learning Approach for Indian States

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ABSTRACT

Especially in light of growing needs and the pressing need for sustainable resource use, precise energy consumption forecasting forms a foundation of contemporary energy management systems. This research offers a deep learning approach based on Long Short-Term Memory (LSTM) to forecast hourly energy consumption in several Indian states. Using historical usage data, the model is individually trained and assessed for every state to spot trends, patterns, and anomalies. Using preprocessing methods including normalization, missing value imputation, and sequence creation, the model performs well in many areas. Strong predictive accuracy is demonstrated by the top-performing states, including Madhya Pradesh (R^2 = 0.6573) and Dadra and Nagar Haveli (R^2 = 0.6615) .The results indicate that real-time energy demand prediction benefits from LSTM models, which also make decision-making aids for grid stability and policy design .

Keywords

Hourly Energy Forecasting, LSTM, Deep Learning, Time Series Analysis, R^2 Score, Smart Grid, Energy Analytics

1. Introduction

Driven by industrial growth, urbanization, and digital transformation, India's energy infrastructure is expanding at an unmatched rate [1]. Forecasting hourly energy use in this case becomes essential to guarantee effective grid operation, lower power outages, and satisfy peak demand without oversupply [2]. Modelling the non-linear, seasonally influenced, and volatile nature of energy consumption data with conventional statistical models usually falls short [3].

Recent developments in deep learning have made it possible to move toward models capable of recognizing long-term dependencies in sequential data [4]. Particularly successful in time series prediction are LSTM networks, a kind of recurrent neural networks (RNNs) [5]. Using actual data, this initiative investigates the use of LSTM-based models for hourly forecasting of energy consumption across 33 Indian states and union territories [6].

2.Literature Survey

Recent developments in deep learning have made possible a move towards models capable of grasping long-term dependencies in sequential data [7]. Specifically successful in time series forecasting are LSTM networks, a kind of recurrent neural networks (RNNs) [8]. Using actual data, this project looks at the use of LSTM-based models for hourly energy consumption forecasting over 33 Indian states and Union Territories [9]. Other research, including those by Kumar et al., underline how including extraneous factors (e.g., weather, holidays) improves prediction accuracy [10]. Although not included in this analysis, such parameters are flagged for next study [11]. Evaluating state-level models across India distinguishes this project, which offers a nuanced knowledge of regional energy dynamics [12].

3. Methodology

This section describes the model's data, preparation processes, and LSTM design .

3.1 Dataset Description

Indexed by timestamps and sorted by states, the dataset contains hourly energy consumption data .Every entry shows the energy used in a certain hour for a particular state .Before machine learning models were used, the data was organized and cleaned .

3.2 Data Preprocessing

- Forward-fill and backward-fill approaches were used to impute missing values [23].
- Data was normalized utilizing MinMaxScaler to scale values between 0 and 1 [24].
- A sliding window approach generated 24-hour input sequences to forecast the following hour .
- Data was divided into 80% training and 20% testing .

3.3 Model Architecture

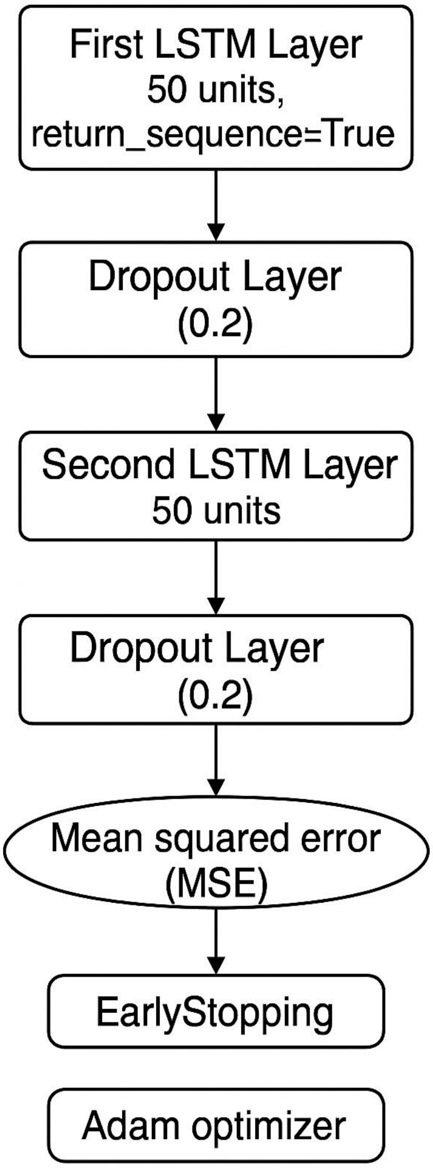


Fig 3.3.1: Sequential Architecture of the Proposed LSTM Network

Design of Model

The suggested model architecture comprises a sequential placement of Long Short-Term Memory (LSTM) layers, dropout layers for regularization, and optimization algorithms to improve performance and avoid overfitting.

First LSTM Layer

With the parameter return_sequences=True to guarantee that the output of this layer can be passed as a sequence to the next LSTM layer, the architecture starts with an LSTM layer of 50 units.This enables the model to keep temporal dependencies among steps.

Dropout Layer

Following the first LSTM layer is a dropout layer with a dropout rate of 0.2 .During training, this layer randomly deletes 20% of the neurons, therefore lowering overfitting and so increasing the generalizing ability of the model.

Second Layer LSTM

50 units make up the second LSTM layer as well. Unlike the first layer, it does not return sequences; rather, it outputs a final hidden state for prediction.

Dropout Layer

After the second LSTM layer, another dropout layer with a rate of 0.2 is introduced to help to lower overfitting.

Loss Function

The Mean Squared Error (MSE) loss function is used to train the model; it is appropriate for regression problems and guarantees that the predicted values are as close as possible to the real target values.

Early Stop

To stop training when the model performance on the validation set ceases enhancing, so avoiding needless calculations and overfitting, EarlyStopping mechanism is included .

Optimizer

Model training uses the Adam optimizer, which offers an adaptive learning rate and combines the benefits of AdaGrad and RMSProp to give quicker convergence and stable training.

This design offers techniques to maximize performance and generalize better while also capturing temporal dependencies in sequential data.

4. Results and Analysis

Using the R^2 Score metric, which assesses the percentage of variance explained by the model, the LSTM model was tested .

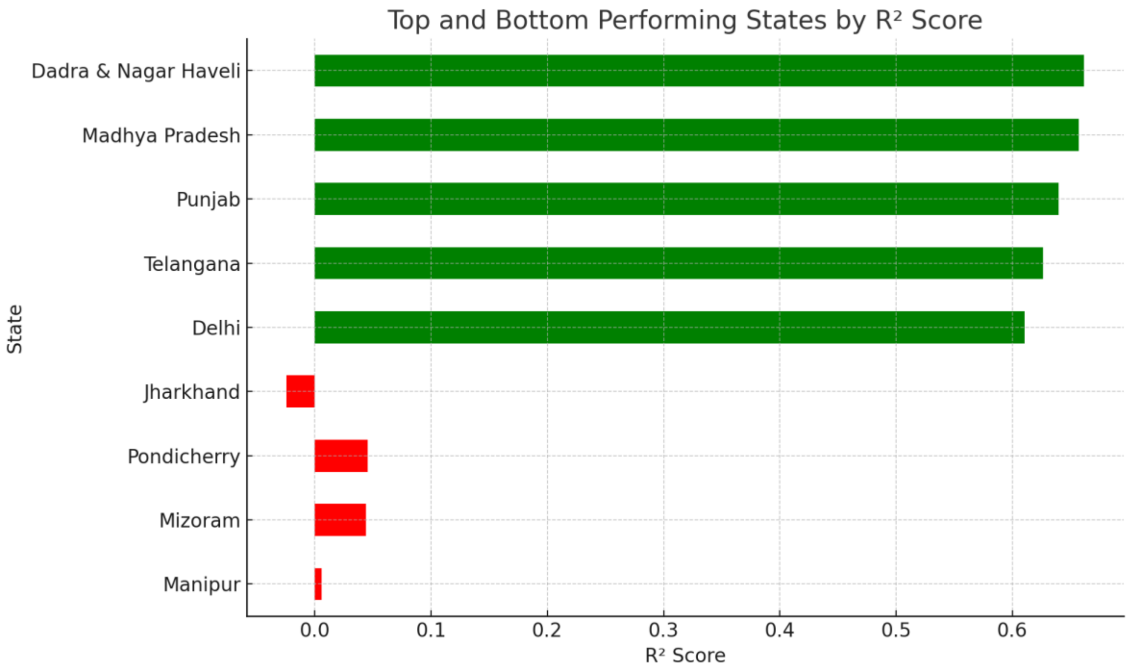
Leading states with their particular R^2 scores:

S.NO	STATE	ACCURACY
1.	Punjab	0.6400
2.	Haryana	0.6004
3.	Rajasthan	0.0923

4.	Delhi	0.6105
5.	Uttar Pradesh(UP)	0.5630
6.	Uttarakhand	0.6080
7.	Himachal Pradesh(HP)	0.5529
8.	Jammu & Kashmir(J&K)	0.0394
9.	Chandigarh	0.5826
10.	Chattisgarh	0.2515
11.	Gujarat	0.3921
12.	Madya Pradesh(MP)	0.6573
13.	Maharashtra	0.4370
14.	GOA	0.4345
15.	Dadra and Nagar Haveli(DNH)	0.6615
16.	Andhra Pradesh	0.6059
17.	Telangana	0.6264
18.	Karnataka	0.6085
19.	Kerala	0.4675
20.	Tamil Nadu	0.2526
21.	Pondicherry	0.0455
22.	Bihar	0.4622
23.	Jharkhand	-0.0244
24.	Odisha	0.5334
25.	West Bengal	0.4847
26.	Sikkim	0.4560

27.	Arunachal Pradesh	0.0257
28.	Assam	0.5234
29.	Manipur	0.0058
30.	Meghalaya	0.4854
31.	Mizoram	0.0440
32.	Nagaland	0.0268
33.	Tripura	0.3647

Table 4.0.1: State-wise Analysis

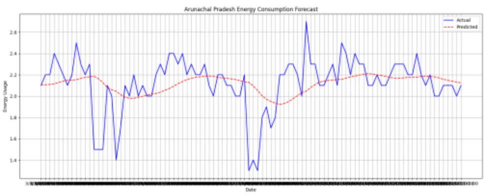


Graph 4.0.2: Top and Bottom Performing States by R^2 Score

4.1 Custom LSTM Evaluation

Better generalization of the model came from the smooth energy consumption patterns and bigger datasets seen in high-performing states .Low-scoring areas, on the other hand, were plagued by noisy data or sporadic sightings .

4.2 State-wise Forecast Visualization:



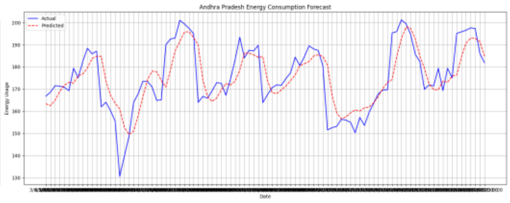
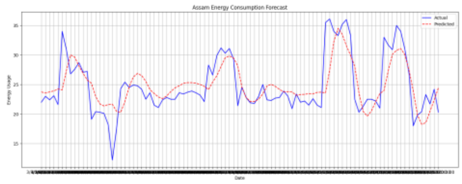


Fig 4.3.1: Forecast Plot for Andhra Pradesh Fig 4.3.2: Forecast Plot for Arunachal Pradesh



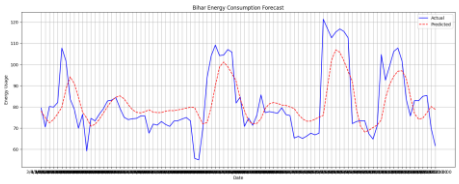
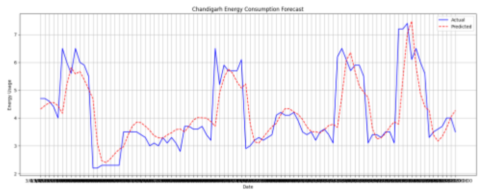


Fig 4.3.3: Forecast Plot for Assam Fig 4.3.4: Forecast Plot for Bihar



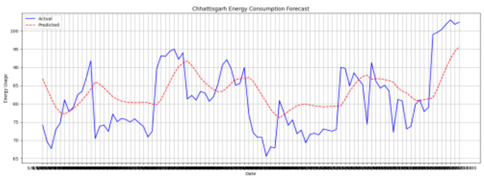
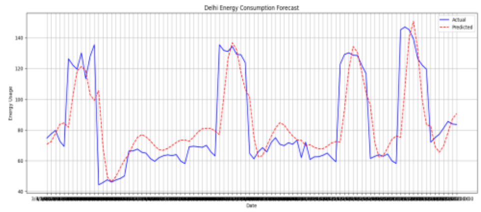


Fig 4.3.5: Forecast Plot for Chandigarh Fig 4.3.6: Forecast Plot for Chhattisgarh



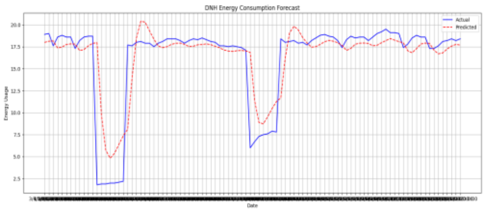


Fig 4.3.7: Forecast Plot for Delhi Fig 4.3.8: Forecast Plot for Dadra and Nagar Haveli

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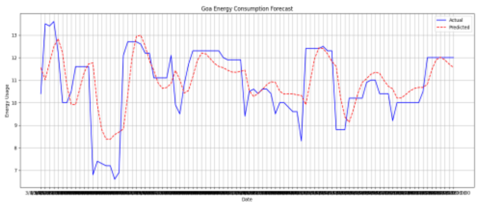


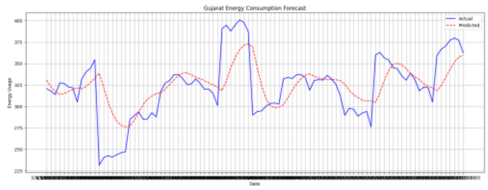
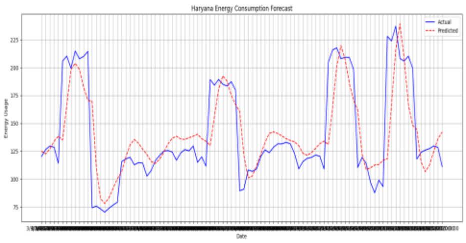


Fig 4.3.9: Forecast Plot for GOA Fig 4.3.10: Forecast Plot for Gujarat



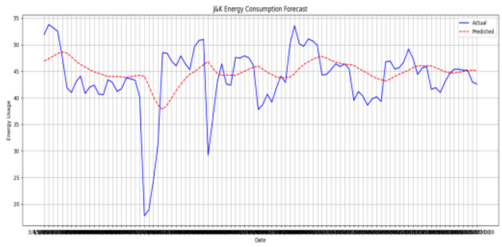
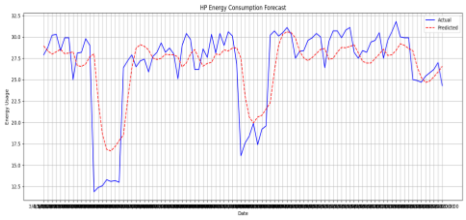


Fig 4.3.11: Forecast Plot for Haryana Fig 4.3.12: Forecast Plot for Jammu & Kashmir



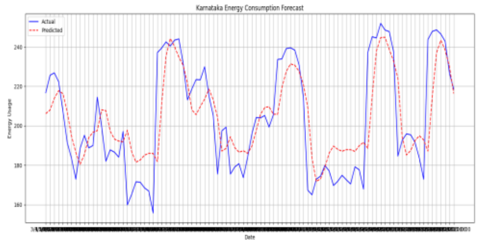
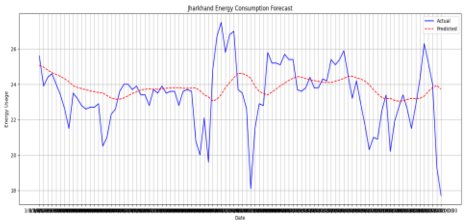


Fig 4.3.13: Forecast Plot for Himachal Pradesh Fig 4.3.14: Forecast Plot for Karnataka



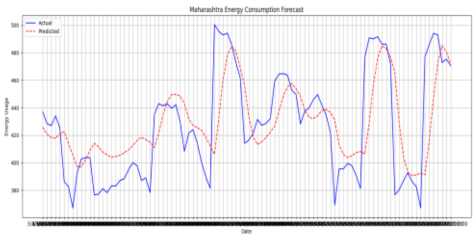
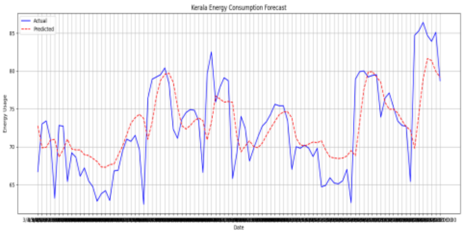


Fig 4.3.15: Forecast Plot for Jharkhand Fig 4.3.16: Forecast Plot for Maharashtra



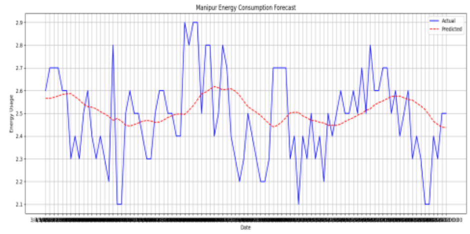
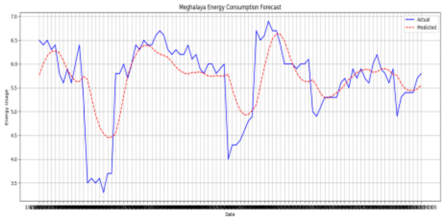


Fig 4.3.17: Forecast Plot for Kerala

Fig 4.3.18: Forecast Plot for Manipur



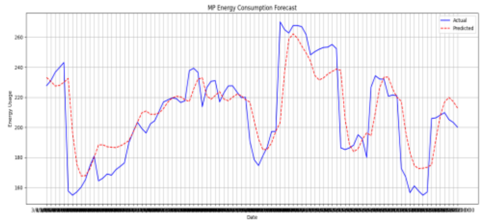
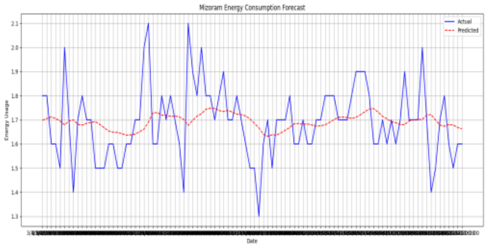


Fig 4.3.19: Forecast Plot for Meghalaya

Fig 4.3.20: Forecast Plot for Madhya Pradesh



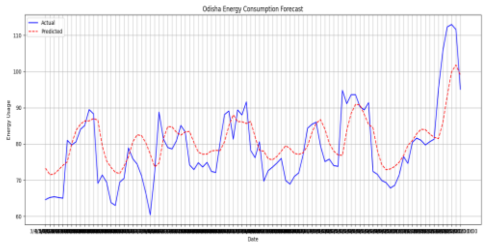
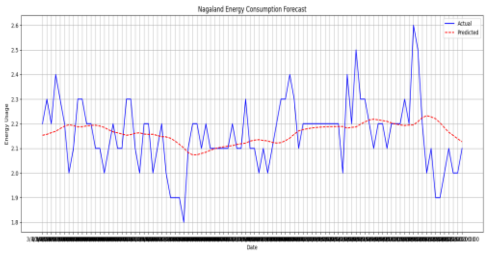


Fig 4.3.21: Forecast Plot for Mizoram

Fig 4.3.22: Forecast Plot for Odisha



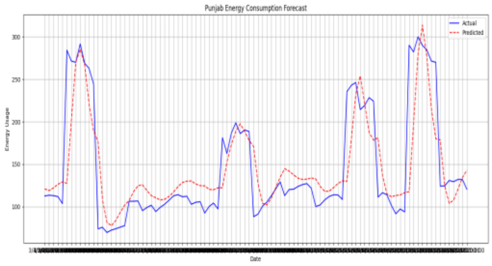


Fig 4.3.23: Forecast Plot for Nagaland

Fig 4.3.24: Forecast Plot for Punjab

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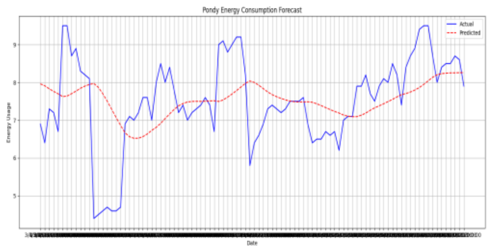


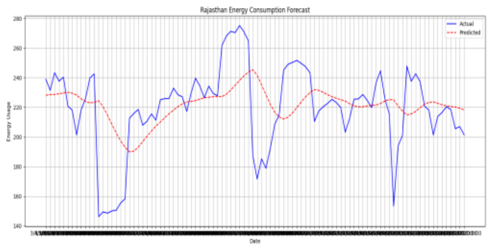
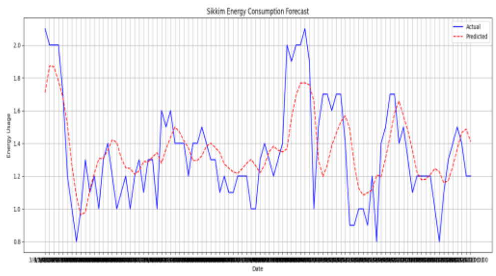


Fig 4.3.25: Forecast Plot for Pondicherry

Fig 4.3.26: Forecast Plot for Rajasthan



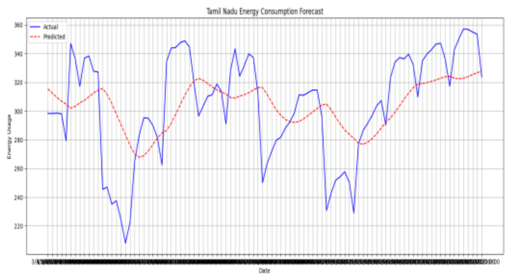
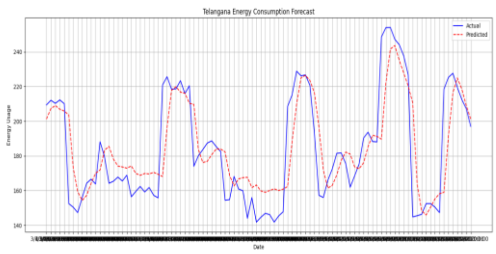


Fig 4.3.27: Forecast Plot for Sikkim

Fig 4.3.28: Forecast Plot for Tamil Nadu



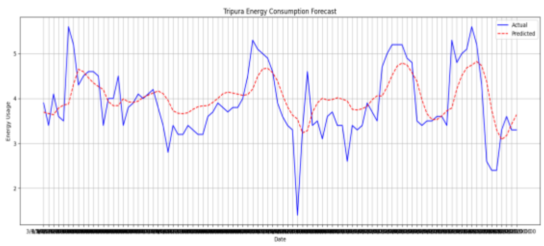


Fig 4.3.29: Forecast Plot for Telangana

Fig 4.3.30: Forecast Plot for Tripura

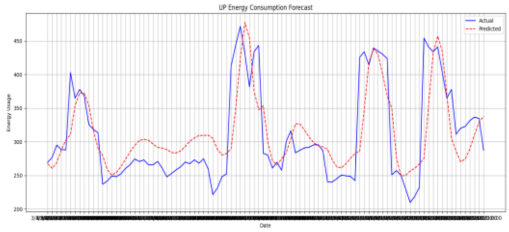


Fig 4.3.31: Forecast Plot for Uttar Pradesh

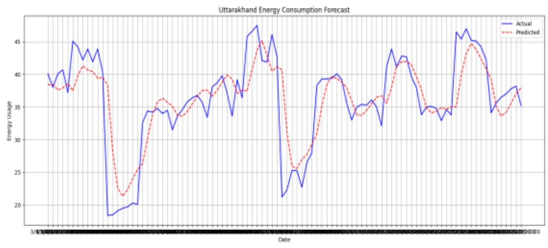


Fig 4.3.32: Forecast Plot for Uttarakhand

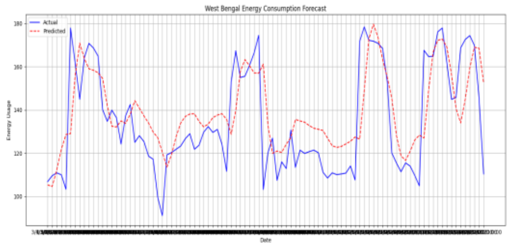


Fig 4.3.33: Forecast Plot for West Bengal

5. Conclusion

This research shows that LSTM models can successfully forecast hourly energy use with remarkable precision across several Indian states . Real-time energy distribution, load balancing, and infrastructural planning have practical ramifications from these models. The discrepancies in accuracy emphasize the need of data quality and the possibilities of hybrid systems . Future research will investigate the inclusion of calendar and weather data as well as the extension of multivariate LSTM algorithms .

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