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Forecasting Index of Industrial Production Sub-Series Using Statistical and Deep Learning Approach

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Abstract: The Index of Industrial Production (IIP) is a key economic indicator that tracks manufacturing activity across various sectors. This paper aims to predict the IIP for three sub-series—Mining, Manufacturing, and Electricity—using both conventional statistical methods and deep learning approaches, analyzing data from April 2012 to September 2022. Model performance is evaluated by comparing Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE)[1]. The results show that the RNN model outperforms other models for all three sub-series, and is used to forecast these sub-series from October 2022 to September 2023.

Keywords: *IIP, Mining, Manufacturing, Electricity, SARIMA, FFNN, RNN, LSTM, Forecasting.*

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I. INTRODUCTION

The Index of Industrial Production (IIP) is a key economic indicator that measures trends in industrial output over time, based on a chosen base year. It reflects the relative change in physical production in industries during a specified year compared to the previous year. The IIP covers three major sub-sectors: Mining, Manufacturing, and Electricity. Policymakers, economists, analysts, and businesses closely monitor these figures to assess industrial growth and inform decisions. This study aims to provide a reliable economic indicator of industrial growth, using historical IIP data as a reference for future IIP releases. Statistical models like ARIMA and deep learning models have been applied to the IIP sub-series, and the best model is evaluated based on error measures such as Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE)[2]. Predictions are made for the next 12 months for the Mining, Manufacturing, and Electricity sub-sectors using the best-performing model.

II. LITERATURE REVIEW

Rani, SA Jyothi, and N. Chandan Babu (2020): "This paper presents the forecasting of rice production (in million tonnes) using Auto Regressive Integrated Moving Averages (ARIMA), Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN). The models are evaluated based on Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results indicate that CNN outperforms ARIMA, RNN, and MLP in predicting rice production[3].

Salam Shantikumar Singh, T. Loidang Devi, Tanusree Deb Roy (2016): "The industrial sector plays a crucial role in India's economic growth, with the composition and production of goods influenced by various factors. These factors can cause short-term (seasonal) and long-term (trend) fluctuations in the Index of Industrial Production (IIP). The primary objective of this study is to analyze the impact of seasonal trends on the IIP in India. Using data from the National Data Sharing & Accessibility Policy (NDSAP), which includes the general IIP and 26 industrial sub-sectors, the study employs the ARIMA (p, d, q) time series model to assess these variations. The results indicate that both seasonal and trend effects are present in the IIP, and a future forecast is made after adjusting for these fluctuations." [4].

III. OBJECTIVES OF THE STUDY

- To fit the model using the ARIMA method

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- To fit the model using the Deep Learning Method-FFNN, RNN, and LSTM, using python code.

- To Identify the best model by comparing MSE, MAE, and RMSE out of all fitted SARIMA and Deep learning models.

- To forecast the IIP values for all three sub-series Mining, Manufacturing, and Electricity for the next 12 months using best-fit model.

IV. RESEARCH METHODOLOGY AND RESULTS

- *Data Source:*

The study considers the Index of Industrial Production data, published by the Ministry of Statistics and Programme Implementation (MOSPI). This study examines the above-mentioned objectives at all Indian levels. The period of study is from April 2012 to September 2022 (A total of 126 observations). IIP values over months for all three sub-series Mining, Manufacturing, and Electricity have been used.

"The results of forecasting are presented using different methods. The methods are compared using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) which are given below" [1]:

$$MSE=1/n \sum (Yt-Ft)2$$

$$MAE=1/n \sum |Yt-Ft|$$

$$\textbf{RMSE}= \sqrt{1/n \sum (Yt - Ft)2}$$

Where Yt is the actual value, Ft is the fitted value and n is the number of months used as forecasting period.

- *ARIMA Model:*

"The development of the ARIMA model for a single variable involves identification, estimation, verification, and forecasting. Each of these steps is now explained for all the IIP's three sub-series datasets" [1].

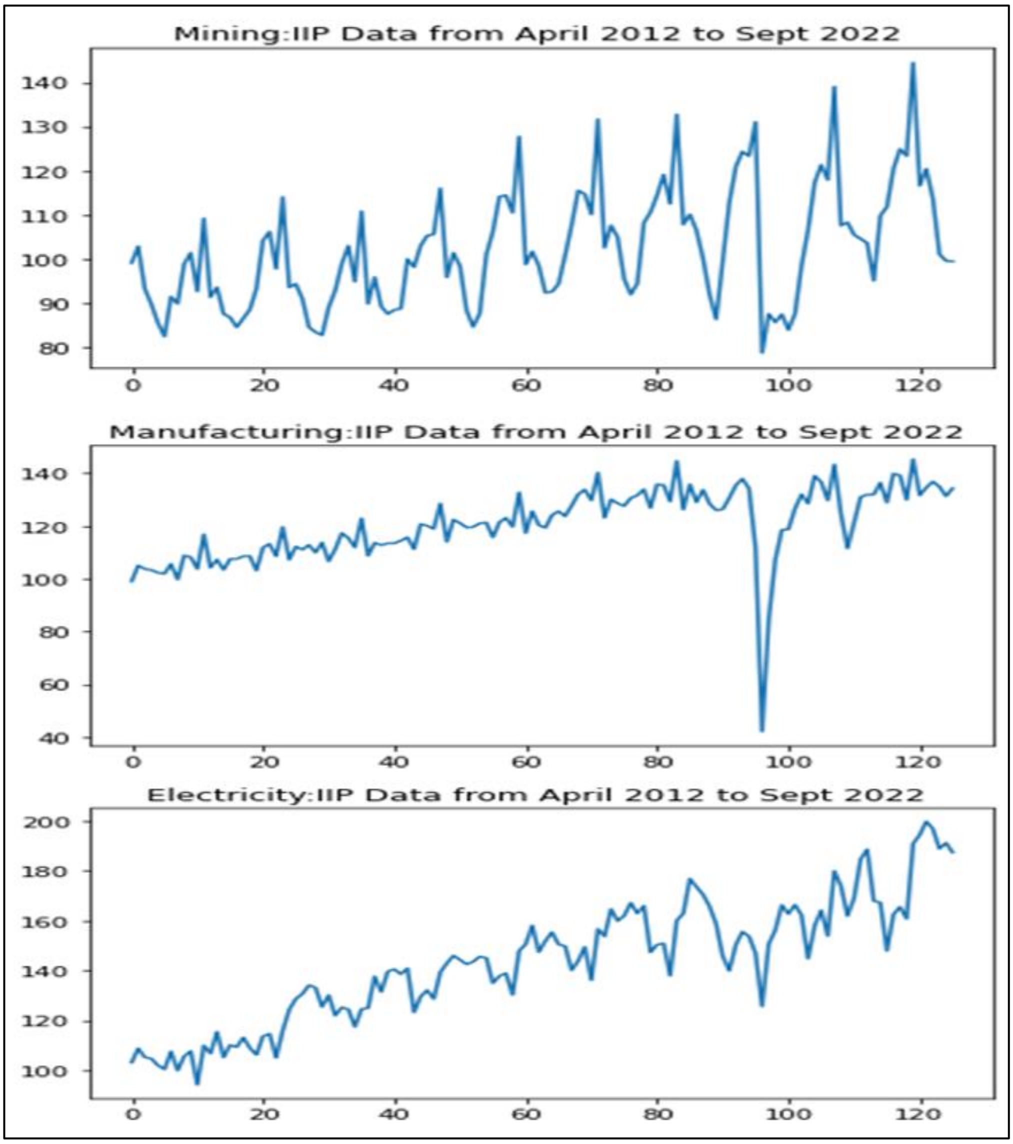

Fig 1 Trends of IIP Data from April 2012 to Sept 2022 for all 3 Sectors

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“First examined whether the data is stationary or not using the Dickey-fuller Test for IIP’s three data series- Mining, Manufacturing, Electricity as shown in Table 1 and the results show that the data is not stationary for all the sub-series. Therefore, the data is converted into stationary by using the first or second-order difference of the datasets.

Table 1 Result of Dickey-Fuller Test

Dataset	**p-value**	**Result**
Mining	0.886	if above 0.05, data is not stationary
Manufacturing	0.623	if above 0.05, data is not stationary
Electricity	0.892	if above 0.05, data is not stationary

To prevent overfitting in neural networks, we divided the original dataset into training and testing sets. We tested different combinations of these datasets across the following neural network architectures:

Feed Forward with splits of [70%, 30%], [75%, 25%], and [80%, 20%]; RNN with splits of [70%, 30%], [75%, 25%], and [80%, 20%]; and LSTM with splits of [70%, 30%], [75%, 25%], and [80%, 20%]. These analyses were conducted across three different data series: Mining, Manufacturing, and Electricity for the training datasets and the results are presented in Table 2.

In addition, models are fitted using different specifications as described below.

- Activation function: Rectified Linear Unit;
- Validation Generator: Timeseries Generator;
- Batch and Sequence Size: 1 and 12.

The following three metrics— MSE, MAE, and RMSE, are used to compare the methods.

Table 2 Test Accuracy: (Training Dataset)

			Mining			**Manufacturing**			**Electricity**		
Model Name	Specification	Training Dataset	MSE	MAE	RMSE	MSE	MAE	RMSE	MSE	MAE	RMSE
Feed Forward	DL (64) DL (32) DL (1)	70%	5.61	1.84	2.37	21.31	3.71	4.61	18.95	3.52	4.35
Feed Forward	**DL (64) DL (32) DL (1)**	**75%**	**10.54**	**2.62**	**3.24**	**21.43**	**3.62**	**4.62**	**26.05**	**4.13**	**5.10**
Feed Forward	DL (64) DL (32) DL (1)	80%	16.92	2.83	4.11	95.25	4.87	9.75	33.63	4.45	5.79
RNN	Simple RNN (64) DL (1)	70%	6.73	2.10	2.59	9.97	2.58	3.15	9.72	2.37	3.11
RNN	**Simple RNN (64) DL (1)**	**75%**	**3.02**	**1.40**	**1.73**	**7.48**	**2.19**	**2.73**	**6.12**	**1.90**	**2.47**
RNN	Simple RNN (64) DL (1)	80%	6.21	2.04	2.49	60.43	4.39	7.77	6.46	1.81	2.54
RNN	Simple RNN (64) DL (32) DL (1)	70%	7.95	2.30	2.82	7.58	2.25	2.75	13.90	3.07	3.72
RNN	Simple RNN (64) DL (32) DL (1)	75%	3.72	1.53	1.92	15.62	3.20	3.95	6.14	1.88	2.47
RNN	Simple RNN (64) DL (32) DL (1)	80%	3.61	1.50	1.90	58.13	4.99	7.62	7.83	2.12	2.79
LSTM	LSTM (50)	70%	24.60	3.86	4.95	13.29	2.86	3.64	16.88	3.36	4.10

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	LSTM (50) DL (1)										
LSTM	**LSTM (50) LSTM (50) DL (1)**	**75%**	**15.54**	**3.18**	**3.94**	**34.12**	**4.91**	**5.84**	**23.14**	**4.01**	**4.81**
LSTM	LSTM (50) LSTM (50) DL (1)	80%	6.21	2.04	2.49	89.04	4.80	9.43	32.23	4.03	5.67
LSTM	LSTM (50) LSTM (50) DL (32) DL (1)	70%	16.05	3.13	4.00	14.37	3.15	3.79	33.80	4.77	5.81
LSTM	LSTM (50) LSTM (50) DL (32) DL (1)	75%	20.47	3.54	4.52	23.99	3.84	4.89	44.76	5.46	6.69
LSTM	LSTM (50) LSTM (50) DL (32) DL (1)	80%	17.22	3.06	4.15	81.02	4.87	9.00	32.04	4.27	5.66

Referring to Table 2, it becomes evident that the MSE, MAE, and RMSE values are consistently minimized when 75% of the training observations are used. Consequently, it was decided that 75% of the observations would serve as the training dataset, while the remaining 25% would be designated as the testing dataset for the execution of different models across all series, namely Mining, Manufacturing, and Electricity. With the adoption of the 75% training dataset, SARIMA models were implemented for all three data series -Mining, Manufacturing, and Electricity which are shown in Tables 3, 4, and 5.

Table 3 Mining-ARIMA Best Model Identification Results

```
Best model:  ARIMA(1,1,1)(0,1,1)[12]
Total fit time: 5.026 seconds
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                    y   No. Observations:                 94
Model:             SARIMAX(1, 1, 1)x(0, 1, 1, 12)   Log Likelihood                -214.767
Date:                            Fri, 05 May 2023   AIC                            437.535
Time:                                    20:40:36   BIC                            447.112
Sample:                                         0   HQIC                           441.377
                                             - 94
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.5788      0.168      3.449      0.001       0.250       0.908
ma.L1         -0.8980      0.099     -9.084      0.000      -1.092      -0.704
ma.S.L12      -0.4885      0.163     -3.003      0.003      -0.807      -0.170
sigma2        11.1774      1.780      6.279      0.000       7.688      14.666
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                 0.32
Prob(Q):                              0.90   Prob(JB):                         0.85
Heteroskedasticity (H):               1.54   Skew:                            -0.15
Prob(H) (two-sided):                  0.27   Kurtosis:                         3.09
===================================================================================
```

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Table 4 Manufacturing-ARIMA Best Model Identification Results

```
Best model:  ARIMA(0,1,1)(1,1,1)[12]
Total fit time: 13.479 seconds
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                    y   No. Observations:                 94
Model:             SARIMAX(0, 1, 1)x(1, 1, 1, 12)   Log Likelihood                -190.704
Date:                            Fri, 05 May 2023   AIC                            389.409
Time:                                    20:55:31   BIC                            398.986
Sample:                                         0   HQIC                           393.251
                                             - 94
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.6819      0.074     -9.239      0.000      -0.827      -0.537
ar.S.L12      -0.2250      0.186     -1.207      0.227      -0.590       0.140
ma.S.L12      -0.8000      0.242     -3.310      0.001      -1.274      -0.326
sigma2         5.2619      1.067      4.933      0.000       3.171       7.353
===================================================================================
Ljung-Box (L1) (Q):                   0.08   Jarque-Bera (JB):                 5.20
Prob(Q):                              0.78   Prob(JB):                         0.07
Heteroskedasticity (H):               2.19   Skew:                            -0.36
Prob(H) (two-sided):                  0.05   Kurtosis:                         4.02
===================================================================================
```

Table 5 Electricity-ARIMA Best Model Identification Results

```
Best model:  ARIMA(1,1,0)(0,1,1)[12]
Total fit time: 4.367 seconds
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                    y   No. Observations:                 94
Model:             SARIMAX(1, 1, 0)x(0, 1, [1], 12)   Log Likelihood                -242.667
Date:                            Fri, 05 May 2023   AIC                            491.334
Time:                                    21:02:05   BIC                            498.517
Sample:                                         0   HQIC                           494.216
                                             - 94
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.2211      0.128     -1.731      0.084      -0.472       0.029
ma.S.L12      -0.7131      0.162     -4.395      0.000      -1.031      -0.395
sigma2        21.0916      3.160      6.675      0.000      14.899      27.284
===================================================================================
Ljung-Box (L1) (Q):                   0.04   Jarque-Bera (JB):                 5.01
Prob(Q):                              0.84   Prob(JB):                         0.08
Heteroskedasticity (H):               1.54   Skew:                            -0.58
Prob(H) (two-sided):                  0.27   Kurtosis:                         3.40
===================================================================================
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The best models are Mining-SARIMA (1,1,1) (0,1,1) [12], Manufacturing- SARIMA (0,1,1) (1,1,1) [12], Electricity-SARIMA (1,1,0) (0,1,1) [12].

After fitting the SARIMA model, the other models FFNN, RNN, and LSTM were fitted by considering training and testing split of [75%,25%] using Python code. The FFNN, RNN, and LSTM are executed using the commands called Sequential, Simple RNN, and LSTM in Python. The Actual Vs. Fitted values have been plotted for the Mining series for all the models with [75%, 25%] split shown in Fig. 2. The blue trend indicates the mining IIP values, the orange trend indicates the predicted training values and the green trend indicates the predicted testing values.

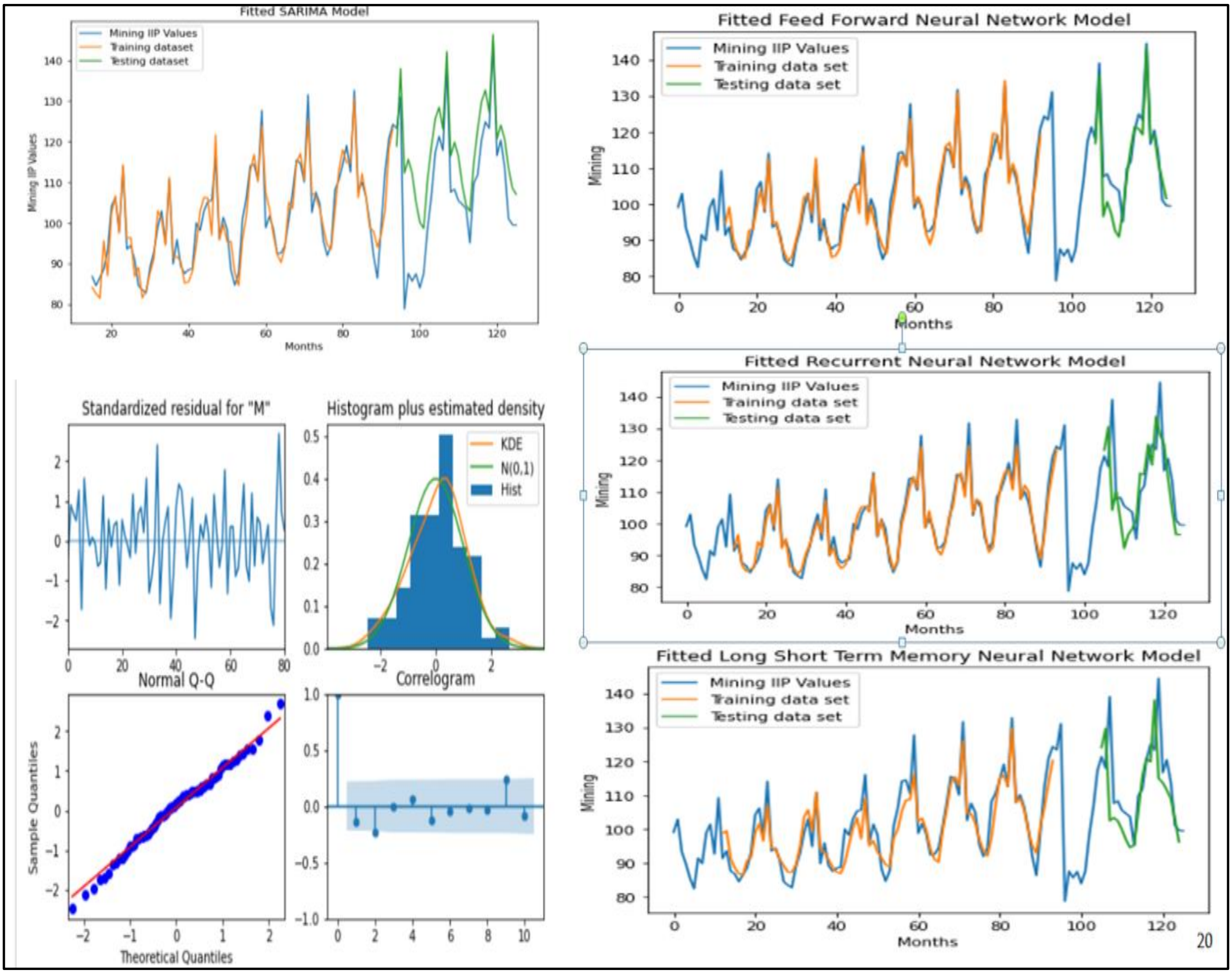

Fig 2 Actual vs Fitted Values for Mining Series
(Both Training and Testing Have Been Plotted for all the Models i.e. ARIMA, FFNN, RNN, and LSTM)

The above Fig. 2, clearly shows that the SARIMA, FFNN, and RNN model fits well for training datasets whereas RNN and LSTM models fit well for testing data. Therefore, the accuracy of projection is also quantified for the testing dataset by calculating the MSE, MAE, and RMSE of the testing dataset of the mining series.

Table 6 Mining: Test Accuracy

Model Name	Specification	Testing Data Set	MSE	MAE	RMSE
SARIMA	-	25%	137.92	9.14	11.74
Feed Forward	Dense Layer-64 Dense Layer-32 Dense Layer-1	25%	38.72	4.82	6.22
RNN	**Simple RNN-64 Dense Layer-1**	**25%**	**24.47**	**4.20**	**4.94**
LSTM	LSTM (50) LSTM (50) Dense Layer-1	25%	78.68	7.83	8.87

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From above Table 6, we observe that MSE, MAE, and RMSE are the least for the RNN model. Therefore, from Table 6 and Table 2, we conclude that RNN (SimpleRNN-64, Dense Layer-1) is the best fit for testing as well as training datasets of mining data series. Hence, we conclude that RNN (SimpleRNN-64, Dense Layer-1) model outperforms the other models and will be used for forecasting the mining data series.

Similarly, The Actual Vs. Fitted values have been plotted for the Manufacturing series for all the models with [75%, 25%] split shown in Fig. 3. The blue trend indicates the manufacturing IIP values, the orange trend indicates the predicted training values and the green trend indicates the predicted testing values.

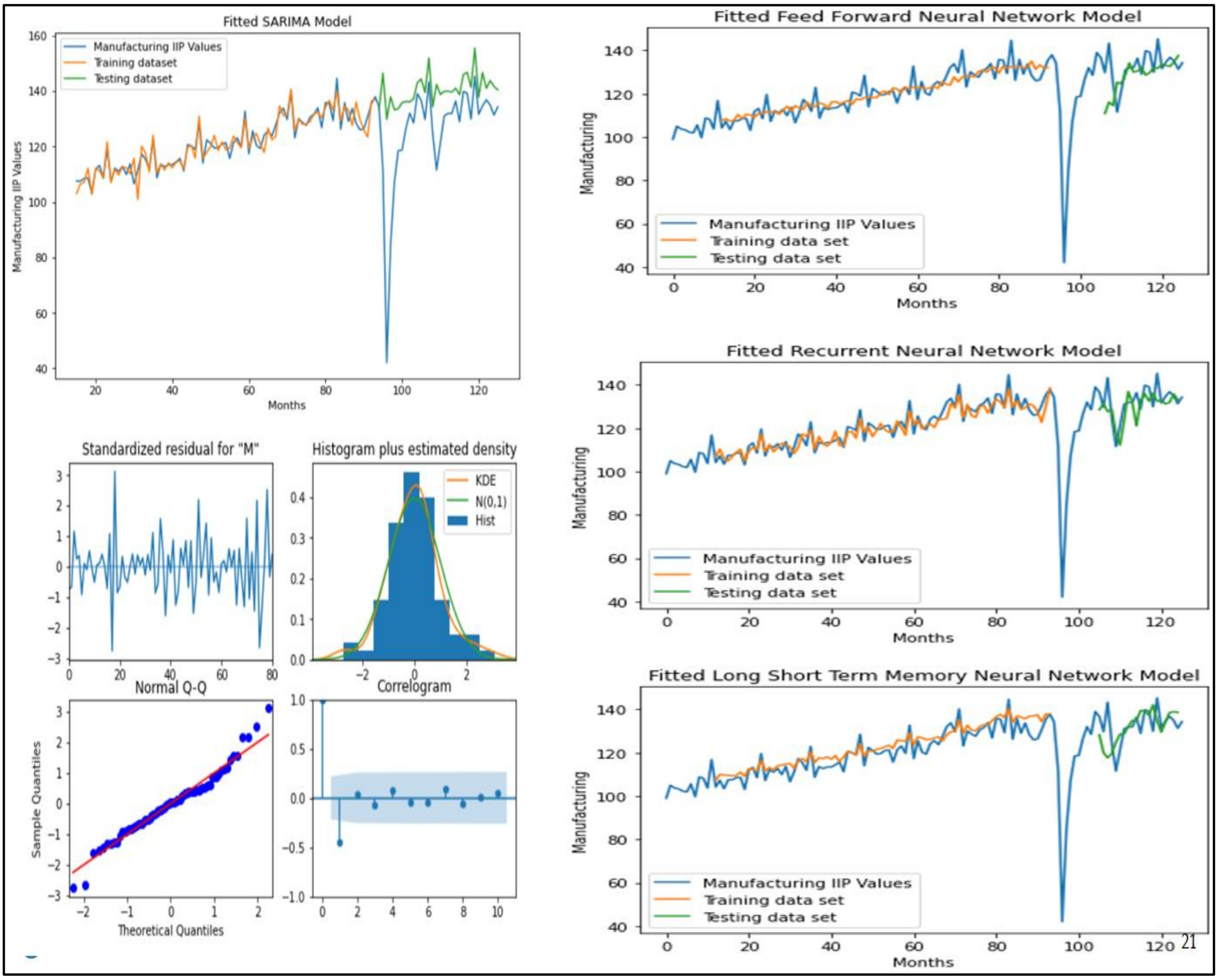

Fig 3 Actual vs Fitted Values for Manufacturing Series

(Both Training and Testing Have Been Plotted for all the Models i.e. ARIMA, FFNN, RNN, and LSTM)

The above Fig 3 clearly shows that the SARIMA, RNN model fits well for training datasets whereas only the RNN model fits well for testing data. Therefore, the accuracy of projection is also quantified for the testing dataset by calculating MSE, MAE, and RMSE to get the accuracy of the testing dataset of the manufacturing series.

Table 7 Manufacturing-Test Accuracy

Model Name	Specification	Testing Data Set	MSE	MAE	RMSE
SARIMA	-	25%	137.92	9.14	11.74
Feed Forward	Dense Layer-64 Dense Layer-32 Dense Layer-1	25%	38.72	4.82	6.22
RNN	**Simple RNN-64 Dense Layer-1**	**25%**	**24.47**	**4.20**	**4.94**
LSTM	LSTM (50) LSTM (50) Dense Layer-1	25%	78.68	7.83	8.87

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From Table 7 we observe that MSE, MAE, and RMSE are the least for the RNN model. Therefore, from Table 7 and Table 2, we conclude that RNN (SimpleRNN-64, Dense Layer-1) is the best fit for testing as well as the training dataset of the Manufacturing data series. Hence, we conclude that the RNN (SimpleRNN-64, Dense Layer-1) model outperforms the other models and will be used for forecasting the manufacturing data series. Similarly, The Actual Vs. Fitted values have been plotted for the Electricity series for all the models with [75%, 25%] split shown in Fig 4. The blue trend indicates the electricity IIP values, the orange trend indicates the predicted training values and the green trend indicates the predicted testing values.

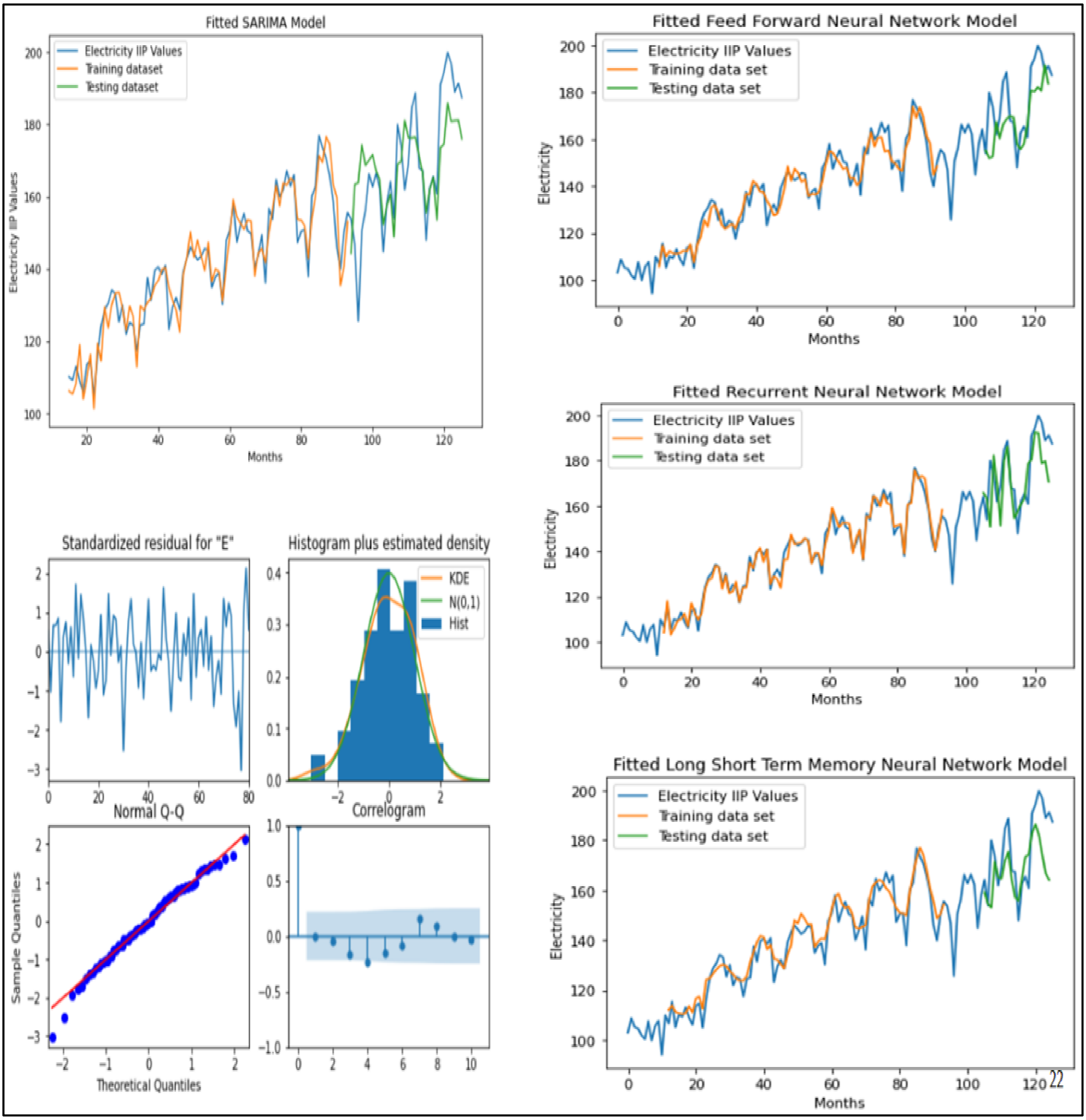

Fig 4 Actual vs Fitted Values for Electricity Series
(Both Training and Testing Have Been Plotted for all the Models i.e. ARIMA, FFNN, RNN, and LSTM)

The above Fig. 4 clearly shows that the SARIMA, FNN, and RNN model fits well for training datasets whereas only the RNN model fits well for testing data. Therefore, the accuracy of projection is also quantified for the testing dataset by calculating MSE, MAE, and RMSE of the testing dataset of the electricity series.

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Table 8 Electricity-Test Accuracy

Model Name	Specification	Testing Data Set	MSE	MAE	RMSE
SARIMA	-	25%	137.92	9.14	11.74
Feed Forward	Dense Layer-64 Dense Layer-32 Dense Layer-1	25%	38.72	4.82	6.22
RNN	**Simple RNN-64 Dense Layer-1**	**25%**	24.47	**4.20**	**4.94**
LSTM	LSTM (50) LSTM (50) Dense Layer-1	25%	78.68	7.83	8.87

From the above Table 8 we observe that MSE, MAE, and RMSE are the least for the RNN model. Therefore, from Table 8 and Table 2, we conclude that RNN (SimpleRNN-64, Dense Layer-1) is the best fit for testing as well as training datasets of the Electricity data series. Hence, we conclude that the RNN (SimpleRNN-64, Dense Layer-1) model outperforms the other models and will be used for forecasting the electricity data series.

V. CONCLUSION

According to the findings, RNN outperforms all other models for all the data series - Mining, Manufacturing, and Electricity. Therefore, forecasted values for all the series-Mining Manufacturing and Electricity are projected using the RNN (SimpleRNN-64, Dense Layer-1) model which is shown below in Table 9.

Table 9 Forecasted Values of IIP from Oct-2020 to Sept-2023 for all three Series

Months	Mining	Manufacturing	Electricity
Oct-22	102.66	127.61	191.08
Nov-22	103.13	127.73	197.19
Dec-22	117.22	127.35	196.83
Jan-23	128.72	129.72	194.27
Feb-23	133.43	124.64	189.90
Mar-23	146.68	132.74	183.75
Apr-23	162.12	124.34	181.36
May-23	171.21	131.89	183.81
Jun-23	183.95	126.58	191.10
Jul-23	177.63	130.28	199.06
Aug-23	172.84	126.90	204.47
Sep-23	160.75	129.01	202.47

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