

Smart E-Logistics for SCM Spend Analysis

Pranav Khedekar, Prof. M. U. Kulkarni

¹Dept of Comp Engg and Information Tech, Veermata Jijabai Technological Institute Mumbai, India

²Dept of Comp Engg and Information, Tech Veermata Jijabai Technological Institute Mumbai, India

Abstract—Currently, there are many literature reviews on the application of predictive analytics in Supply Chain Management (SCM). However, most of them focus only on some specific functions in supply chain management, including Procurement, Demand Management, Logistics and Transportation, or purely technical aspects. The purpose of this paper is, it aims to provide an overview of the outstanding supply chain management functions (SCMF) that apply predictive analytics. Spend analysis is one of the major areas of SCM, in which predictive analytics is applied. LSTM model is created which provides a better accuracy for time series data. The results obtained are compared stating why the above mentioned LSTM approach is better. Along with Spend Analysis training of Printed and Handwritten documents for extraction of required fields is also worked upon. Extracting fields from different document templates (Printed and Handwritten Invoices and Proof of Delivery) was a challenge for which we were able to produce better results and accuracy.

Index Terms—Predictive Analytics, Machine learning, Supply chain management (SCM), Long Short-Term Memory (LSTM), Data Augmentation, Image Pre processing, Form Recognizer

I. INTRODUCTION

Logistics is that part of the supply chain process that plans, implements, and controls the efficient, effective flow and storage of goods, services, and related information from the point-of-origin to the point-of-consumption in order to meet customers' requirements. By sharing data, knowledge, and information with supply chain partners, e-Logistics is a dynamic combination of communication, computing, and collaboration technologies that alter core logistical operations to be customer centric. Delivering the right items to the right customer in the appropriate amounts, at the right time and place, is the ultimate goal of e-logistics. To help decision-makers and foresee certain future events, predictive models employ historical and transactional data to find trends, risks and opportunities within a given set of circumstances. Predictive solutions can be used for a variety of purposes, but they are most valuable when they are customised for a specific kind of operation and built around a set of rules and guidelines designed just for that business. By using predictive solutions to generate supply and demand forecasts, companies will be able to make the right operational decisions in a proactive manner.

This approach can also allow for the re-balancing of assets across any logistic network at a minimal cost.

II. LITERATURE REVIEW

Demand management is the most SCM function using predictive analytics [1]. In fact, the reviewed literature demonstrated a number of contributions addressing the analysis of historical datasets and the capture of real-time demand changes for sensing and anticipating need. Demand forecasting is the precise assessment of a product's demand using the relationship between the product and a group of unrelated input variables.

Data collection: The process of comprehending and compiling data on elements connected to SCM operations, such as sourcing risk, demand forecasts, etc., is known as data collection. However, excessive data will take time to normalise, and inaccurate data will skew the system's overall findings. As a result, choosing the right data source is crucial to the system's performance. It is obvious that the phase of data collecting is the most crucial in the entire system.

Feature extraction: The process of extracting some crucial characteristics from a dataset using several techniques, like cross-validation and REF, is known as feature extraction. As a result, a subset that is derived from the original data will produce a result that is more accurate than the original data. As a result, this feature extraction technique needs to be applied to the acquired data.

Feature selection: The data must be chosen using the feature selection procedure after being divided into subsets with features in order to choose the data with the most crucial characteristic. DT, XG-boost, ACF, and other popular methods could be employed at this stage.

Optimized model generation: After completing the pre-processing steps, the data must now be divided into two sets: the training dataset and the testing dataset. As a result, the training dataset is used to develop the optimised model by identifying the best parameters, and the testing dataset is used to confirm the accuracy of the system output. However, with the exception of partner selection in procurement functions, this dataset decomposition applies to all SCMF research issues. In terms of partner selection, the results will be obtained by directly applying the normalised dataset to a certain method or model.

Prediction/ Classification implement and Evaluation: To detect and anticipate outcomes, such as a risk prediction for SCRM (source risk management), customer engagement (demand sensing), future demand (demand forecasting), etc., testing dataset will be applied to the optimised model. Additionally, the normalised dataset will be directly put to the method or model for partner selection in order to assess the possible risk of the provider.

The datasets included in this paper display a wide range of properties and formats. The variety of datasets originates from various supply chain functions, ranging from text databases to time-series historical datasets and numerical, historical statistics datasets. The time-series dataset is utilised during the data gathering phase as the main data attribute for anticipating demand. Original or raw datasets frequently include unstructured information, redundant attributes, and confusing, incorrect attributes. In order to normalise raw data or pick the data with the most significant characteristics, numerous strategies and algorithms have been utilised during the pre-processing stage, particularly during the Feature selection phrase. The transmission method and differences between the original dataset and the optimised featured/normalized dataset are, however, only fully demonstrated in three studies. The forecasting process can be divided into processing stages.[2] Typically, it may consist the following: •An initial examination of the original time series is conducted with the intention of obtaining high-quality, reliable data after identifying any gaps in the data or the need for time series interpolation; the choice of interpolation technique influences the outcomes of subsequent calculations (i.e. correlation or similarity analysis).

•the use of preprocessing algorithms (for example, to retrieve valuable information, to noise reduction, to extract specific components from processed time series). • an implementation of chosen forecasting algorithm(s) across a predetermined time horizon. • Dedicated error measurements are used to analyse the quality of the prediction findings (for example, root mean square errors, RMSEs). The latest value of the processed series serves as the best predictor in the Wiener process (random walk), which treats daily increments as stationary sequences of independent random numbers, particularly for short-term prediction horizons. The zero order-hold (ZOH) and first order-hold (FOH) approaches can be applied for this purpose. Zero Order denotes a constant function; to fill up the gaps, we interpolate the same value. First order indicates that we can interpolate using a linear function (Line with a slope). Hold refers to keeping the parameters constant until the following sample. Time series with a trend and a random component are smoothed and predicted using the Holt's model. The linear trend in the series "yn" is expressed by the first-order polynomial. Exponentially smoothing is used to control the variable level and its increments. The adaptive Holt's model can be applied by the parameters (weights) adaptation in a moving window. p-step prediction of time series y at the time n is calculated as: In order to produce a Newton series that matches the data, polynomial extrapolation is often done using Lagrange interpolation or Newton's method of finite differences. The generated polynomial can be applied to the data to extrapolate it. Use high-order polynomial extrapolation with caution. With additional k-fold cross validation, the error is reduced and the outcome is obtained considerably more quickly. [3] A class called K-Fold enables you to divide your data into K folds. The advantage of LSTM is that each cell tries to retain the most important information in the data. By using a memory unit known as a cell unit or cell memory for a network, LSTM was developed to correct the exploding and vanishing gradient during training RNN. The model can learn from every output of the sequence data since cells are allowed to remember the results. The most essential three gates of LSTM model: update, forget and output gates.

$$\hat{c}_t = \tanh(W_c [a_{t-1}, x_t] + b_c) \quad (1)$$

$$u_t = \sigma(W_u [a_{t-1}, x_t] + b_u) \quad (2)$$

$$f_t = \sigma(W_f [a_{t-1}, x_t] + b_f) \quad (3)$$

$$o_t = \sigma(W_o [a_{t-1}, x_t] + b_o) \quad (4)$$

$$c_t = u_t * \hat{c}_t + f_t * c_{t-1} \quad (5)$$

$$a_t = o_t * \tanh(c_t) \quad (6)$$

A candidate is calculated using equation 1. The weight w_c and bias b_c are the candidate t 's own parameters. The weight w_u and the bias b_u are the parameters of the update gate u_t , which is calculated in Equation 2. By utilising a sigmoid function, they assist the model in determining when to update the memory cell; if the output of the sigmoid function is close to one, it is updated, and if it is close to zero, it is disregarded. The parameters of the memory cell will be updated by multiplying the output of update gate u_t and candidate t . The forget gate operates in a manner similar to that of the update gate. Equation 3 demonstrates how the model can decide when to erase the data stored in a memory cell by using the forget gate. The weight w_f and the bias b_f are the specifications for the forget gate f_t . Equation 4 calculates the output gate o_t by adding the bias b_o and weight w_o to the current input. By multiplying the update gate by the candidate t and adding it to the forget gate, which is multiplied by the previous cell state c_{t-1} , a new cell state c_t is computed and passed to the following layer using Equation 5 to update the parameters to cell state.



A common metric for determining how accurately a model predicts quantitative data is the root mean square error (RMSE).

Comparing ARIMA and LSTM-based algorithms, the prediction was improved by an average of 85%. Comparison of the effectiveness of ARIMA and LSTM models in terms of lowering error rates is added, and it is a generalisation of the more straightforward Auto Regressive Moving Average. Because the data that was gathered and analysed are non-stationary, ARIMA is chosen to serve as a proxy of conventional forecast modelling. The LSTM approach is employed similarly and as a representation of deep learning-based algorithms due to its use in maintaining and training the features of given data over a longer duration. A type of recurrent neural network called long short-term memory (LSTM) is able to retain values from earlier stages for use in the future.

LSTM-based algorithm improved the prediction by 85% on average compared to ARIMA. There are five major stages in OCR. They are as follows: [5]

1. Digitization
2. Pre-processing
3. Segmentation
4. Feature Extraction
5. Post-processing

- Converting handwriting or text documents into electronic format is what is meant by digitization. The pre-processing stage is the next step for the image.
- Location segmentation and noise reduction involve smoothing, thinning, fixing break-ages, de-skewing, etc. of the image as part of pre-processing.
- Segmentation is the process of removing individual characters from an image.
- Following character separation, each character's unique features—including diagonal, intersection, transition, direction, curve fitting, etc.—are retrieved and transmitted for post-processing.
- Character grouping and error detection are included in the post-processing

OCR recognition rate can be greatly improved using Beizer Curve. [6]

Less than 30% of the actual number of characters in the text image can be recognised before repair, and there are numerous mistakes. All characters may be recognised in the text image after correction, and there are fewer mistakes. Traditional paper text, especially books, will generate apparent bending distortion during the picture collecting process, affecting the recognition accuracy of OCR. This paper suggests a text repair technique based on a bezier curve. As part of a deep learning strategy, text regions are detected by utilising ROI to construct border boxes, and text is then retrieved using convolution neural networks. [7]

The following phases make up the suggested strategy:

Image acquisition: In image acquisition, images that will be processed are stored in a local file and read one at a time as they are processed. The RGB channel is used to store the images.

Pre-processing: A unique dataset with 467 photos is made for an experiment. Phases for testing and training are separated from the dataset. 258 photos from the collection are tested, and 209 images are trained for text extraction and identification. Results from the data set are assessed in light of these.

Images are grayscaled at the pre-processing stage. The image is changed to grayscale by multiplying the RGB values by 0.29, 0.587, and 0.114, respectively. The Otsu method is used for dimensionality (shape, width, and height) and layer reduction to identify each pixel. The algorithm outputs a single intensity threshold that divides pixels into two groups, foreground and background.

Binarization:

Binarization is the process of taking a grayscale image and turning it into one that is incredibly differentiating, thereby reducing the amount of information it contains from 256 shades of grey to one that is extremely contrasting and disguised as a binary image.

By measuring background brightness and the depth of the black area along the line, adaptive binarization can determine the best binarization parameters for each individual line segment. Higher acknowledgement precision will be attained as a result of the lines and words being precisely separated.

Segmentation:

The text region will be recognised and detected during the segmentation phase utilising the region of interest. By assembling related pixels with comparable attributes, text and non-text regions are separated. The text is detected from the region of interest (ROI) by constructing a border box once the text region has been identified by taking into account the x, y plane of the text region.

Edges in the text section of the image are found using width and height, which are expressed as pixel coordinates, and returned to ROI. Bounding boxes are drawn using pixel coordinates.

Feature Extraction:

Convolution and pooling procedures of CNN are used in feature extraction to identify the optimum features. Before extracting the text from the blurred and unblurred photos, the system is trained on the images. With the aid of a convolution neural network, the text will be retrieved (CNN). Each character in the text created by the bounding box is recognised and displayed over an image using trained characters.

The two operations that make up a traditional CNN are convolution and pooling, and the input picture can instantly be convolved with different convolution kernels. The output of this operational series is typically linked to a fully linked layer, which is fundamentally comparable to a multilayer perceptron neural network (MCP)

III. PROPOSED ARCHITECTURE

A. INVOICE RECONCILIATION MODULE:

Upload the scanned copy of POD (Proof of Delivery) and Invoice.

Image Uploaded to Blob Storage. (Blob storage is a feature in Microsoft Azure that lets developers store data in Microsoft's cloud platform).

Image accessed from the Blob storage and OCR (Optical Character Recognition) is applied on the uploaded POD and Invoice.

Text from the upload POD or Invoice is extracted and is printed in form of output.

Once the data from both the uploaded documents is collected, they are compared and based on which the match confidence is calculated and along with that the accuracy on which the field is extracted by the OCR.

B. STEPS

1. Model Training and Testing:

Labelling and training models using Form Recognizer and testing for the same

Form Recognizer:

Creation of a project

Uploading the images to be trained to the blob storage. Labelling the data

Label.json and Ocr.json files would be created after the model is trained.

2. Data Cleaning:

Cleaning the extracted data from new trained models

3. Combine Test And Restructure:

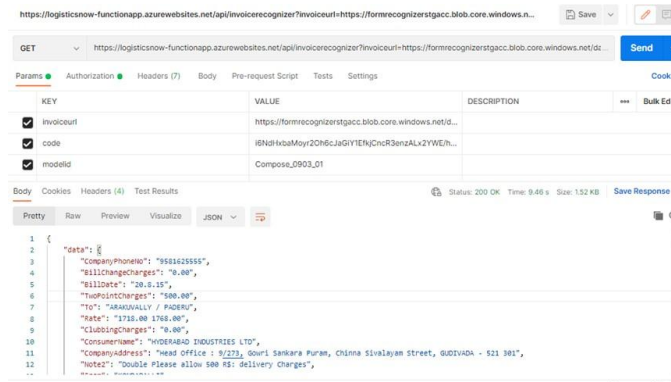
Combine the model with existing model, test for the same. Restructure the data sent to UI

4. Comparison of Values:

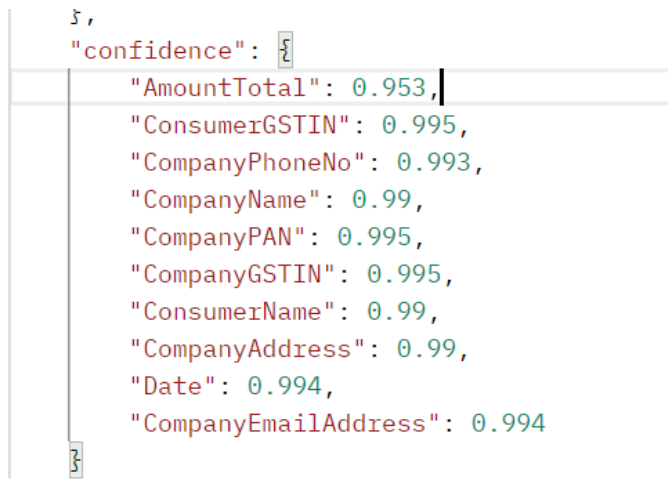
Compare the Invoice and POD, get accurate results. Compare extracted values with Freight Master

5. Match Confidence Calculation: Calculation of match Confidence

For Printed Document: Output: Extraction of Fields



Accuracy Obtained:



The above image states that the fields extracted from the handwritten documents do not obtain desired accuracy. Hence, to deal with this issue two approaches were considered.

C. PREPARATION OF SINGLE MODEL

The Invoices and Proof of Delivery available in real world do not follow a single template. There are multiple templates and multiple different fields which are required to be extracted and placed at different positions.

Creation of a single model decreases the accuracy of the model.

Tag	Estimated Accuracy
Date	100.00%
From	58.30%
InvoiceID	100.00%
To	75.00%
TotalAmount	100.00%
VendorName	100.00%

The above image shows the accuracy of each field extracted when two different types of documents are trained together.

Tag	Estimated Accuracy
Date	100.00%
From	77.80%
InvoiceID	100.00%
To	66.70%
TotalAmount	100.00%
VendorName	100.00%

The above image shows the accuracy of each field extracted when three different types of documents are trained together.

To overcome this issue we came up with a solution of creation of different model for different types of documents and then combine them together to form a single master model.

This approach provided us better accuracy.

D. METHODS

Method 1:

1. Application of Data Augmentation to increase the dataset for training and testing purpose, to get more accurate results.
2. Application of Image Pre-processing Techniques.
3. Then train the obtained images with the help of FormRecognizer.
4. Analyse the Results.
5. This approach did not provide much better accuracy.

Method 2:

1. Train the Model using the Form Recognizer.
2. Analyse the output.
3. If the output is not as accurate as required.
4. Prepare a set of keywords, create an excel file for the same.

City	State	Company Name	Company Address	Company Phone	Company Email
Kodagalli	Kerala	M/S MARYO LIMITED	MENONPADA ROAD, INDORE, KALAKKAD - 578221	02075 62001	SANKARA PURAM, CHINNA SIVAKAYAM STREET, GUDUVADA - 575 301
Kangasode	Tamil Nadu	M/S. JYOTHI LABORATORIES PVT. LTD.	B-100 8TH FLOOR NO.179 NELSON MANICKAM ROAD ANNAMALAI CHEMMAI 600 029	0432 2621111	ADITHYAN LOGISTICS
Coimbatore	Kerala	HECTOR BEVERAGES PRIVATE LIMITED	23B FINCHLEY CASTLE OUTER CIRCLE COOSWORTH LAYOUT WHITEFIELD BENGALURU KARNATAKA 560065	0832 2621111	A.S. TRANSPORT PRIVATE LIMITED
K.G. Chavadi	Kerala	M/S. JYOTHI LABORATORIES LTD.	AMBALA	ANAND ROAD LINES	BLOOD, 8 TH FLOOR NO.179, NELSON MANICKAM ROAD, ANNAMALAI, CHEMMAI - 600 029
Nanakari	K.G. Chavadi	MPL	M/S. JYOTHI LABORATORIES LTD. JAMMU	FOOD SMART MOBILITY PVT LTD	S.P. GOLDEN PVT. LTD.
AMBALA	Nagpur	HYDERABAD INDUSTRIES LTD	NEW INDUSTRIAL DEVELOPMENT AREA MENONPADA ROAD KANUHODE 676 621 DISTT FALAKKAD KERALA	WESTERN CARRIERS	AMBALA B&HC, 1ST FLOOR, OFF HARIYANA MOTER MARKET, C-1 ROAD, AMBALA CTEH, INDIA
BARU	Pune		NO. 42 A, C/O DIA LOGISTIC PVT LTD ROAD NO.3, 1ST PHASE JIGANI INDUSTRIAL AREA BENGALURU BANGALORE KARNATAKA 560036	SAJALI LOGISTICS	5-1 ANAND-DEEP BUILDING, GHAZILOR - 474011 P.O. - 401, DEEPALI BUILDING, 61, NEHRU PLACE, NEW DELHI 110018
SOHAMAN	Nagpur		HECTOR BEVERAGES PVT LTD KASABOLA INDUSTRIAL AREA MYSORE DISTT KARNATAKA	B.D. C & F AGENCIES	2ND FLOOR, PLAT NO. 22, TRENDZ ETERNITY BUILDING, GREEN LAND COLONY, GACHIBOWLI, HYDERABAD, TELANGANA, 500028
COIMBATORE	Bangalore		C/O CRYSTAL MARKETING CORPORATION SHANMUGHUR HYDERABAD 500029	MATHURSHREE ROAD CARRIERS	8708 STRAND ROAD, KOLKATA-8, C/O:759, WAKADEEP BUILDING, LAXMI NAGAR, DISTT CENTER DELHI 110029
Mysore	Bihar		STRAND ROAD KOLKATA B.O WAKADEEP BUILDING LAXMI NAGAR DISTT CENTER DELHI 110029	PANDU ROAD LINES	0 NID 6-B&L, MUTHANG VILL, PATANCHERU MDL, SANGAREDDY DIST, TELANGANA - 502018
ROORKEE	HOWARH		INDUSTRIAL SUPPLIERS MAIN ROAD SHIMOGA SHIMOGA DISTT KARNATAKA (INDIA)	KONARK ROAD LINES LP	DEWASHISH CO.OP. HSG. SOC. LTD. - A-304, KOLSHET ROAD, OFF CHOKAL POWER HOUSE, PHAWNE (W) - 400 607
JAMMU	KOLKATA		DOOSWORTH LAYOUT WHITEFIELD B LDRS 360-368	SOUTHERN CARGO CARRIERS INDIA	NO.32, 2ND CROSS KAUSALPALLYAM NEW EXTENSION BANGALORE - 560002
Phoolpur	KANPUR			GANGA JAMUNA CARRIERS	
VARANASI	BANARSI			M.S.S ROADWAYS	
MYSORE	BANGALORE			HIL	
PAITHAN	ROHTAK			VARUNA INTEGRATED CARRIERS	
Sethuraja	Goa			TO FREIGHT	
MIS	Bengaluru			HEENA ROADLINE	
KADAMOLA	Bhubaneswar			ATHARV LOGISTICS	

5. Once the value is extracted, it will pass through all the keywords present in the list for that particular key.
6. Algorithm will compare the entire extracted string with the keywords and the output which is more similar will be considered.
7. This approach is not mentioned in any of the papers, no paper talks about extracting the proper output if not recognised properly.

Output: Extraction of Fields For Handwritten Documents:

```

"ConsigneeName": "SAPRIDIEMI ENTERPRISES AWASTHI GALI IBRAHIMGANT CHHIBRAMAJI KANNAUJ 209721",
"CompanyName": "B. D. C & F AGENCIES",
"Date": "27/03/2022",
"GSTIN": "09ABYPAA380012X",
"CompanyHeadOffice": "K. 67/05-21, Nati Imli, Varanasi - 221001",
"From": "PhoolpurVNS",
"To": "KANNAUJ",
"CompanyAddress": "5. 8/119 B-1, Sudhakar Road, Khajuri, Varanasi - 221002",
"FSAINo": "12719038000032",
"TruckNo": "HR060-4471",
"CompanyBranchOffice": "Vii Bahadur Singh, New Transport Nagar, Gidda, Gozakhpur Mob .: 0874111101 A-9, Site No. 5, Udayg Kunj, Panki, Kanpur Mob .: 9335747474, 9307371176 B-5, Industrial Area, Naini, Prayagraj - 211008",
"InvoiceNo": "2899",

```

The above image states that the fields extracted from the handwritten documents obtain the desired accuracy.

E. IMPLEMENTATION OF STACKED LSTM:

STEP 1: The transporter Dataset

The dataset contains fields such as symbol, date, spend, high rate, low rate., open rate, volume, average close, average high, average open and average volume. It contains "1257" rows of data.

STEP 2: Plot the obtained dataset and application of Min

– Max scaler. Plot the graph for the gathered dataset using the matplotlib library and get an overview of the data.

Using the Min – Max scaler function convert all the outputs present in the dataset in a range of 0 to 1. 0 represents the smallest value and 1 represents the maximum value and rest of the values present and adjusted between the given range.

STEP 3: Splitting the dataset into test and train dataset. Splitting the dataset into test and train data is an important task. The data being time-series data cannot be distributed across testing and training data randomly. Data used for training and testing is distributed sequentially.

STEP 4: Converting the array into a dataset matrix. Convert the array into dataset matrix and reshape the same.

STEP 5: Reshaping the input which is required as per LSTM.

You always have to give a three-dimensional array as an input to your LSTM network. Where the first dimension represents the batch size, the second dimension represents the number of time-steps you are feeding a sequence. And the third dimension represents the number of units in one input sequence.

STEP 6: Creating a stacked LSTM Model

An LSTM model comprised of multiple LSTM layers.

```
### Create the Stacked LSTM model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM

model=Sequential()
model.add(LSTM(50,return_sequences=True,input_shape=(100,1)))
model.add(LSTM(50,return_sequences=True))
model.add(LSTM(50))
model.add(Dense(1))
model.compile(loss='mean_squared_error',optimizer='adam')
```

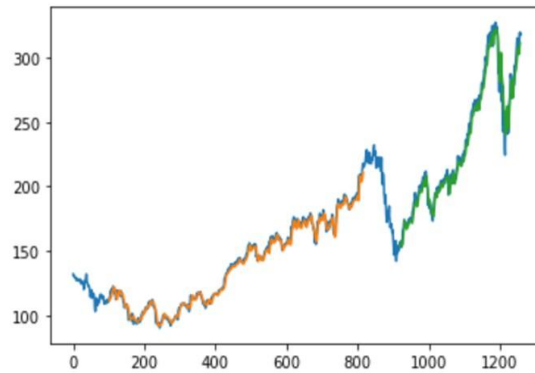
STEP 7: Checking the model summary after training

```
model.summary()
Model: "sequential_3"
-----
Layer (type)                Output Shape                Param #
-----
lstm_7 (LSTM)                (None, 100, 50)            10400
-----
lstm_8 (LSTM)                (None, 100, 50)            20200
-----
lstm_9 (LSTM)                (None, 50)                  20200
-----
dense_3 (Dense)              (None, 1)                   51
-----
Total params: 50,851
Trainable params: 50,851
Non-trainable params: 0
-----
```

STEP 8: Predicting and checking the performance metrics STEP 9: Calculating the RMSE (Root Mean Square Error)

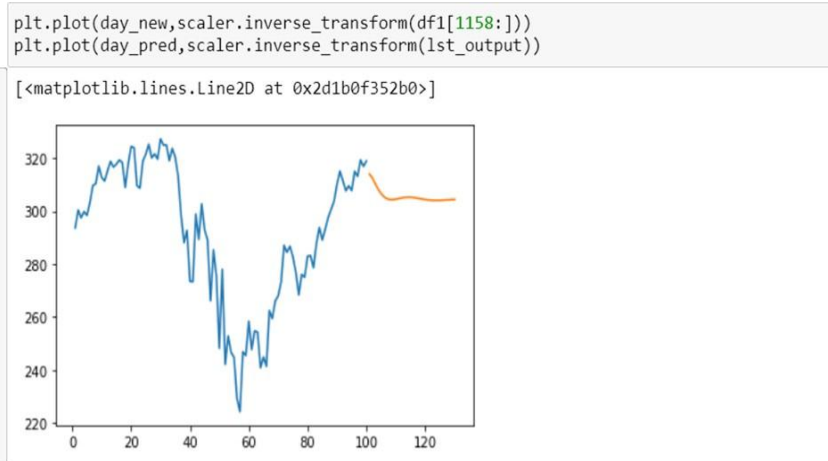
It is required to judge a model’s performance, whether it be during training, cross-validation, or monitoring after deployment

STEP 10: Plotting the predicted output

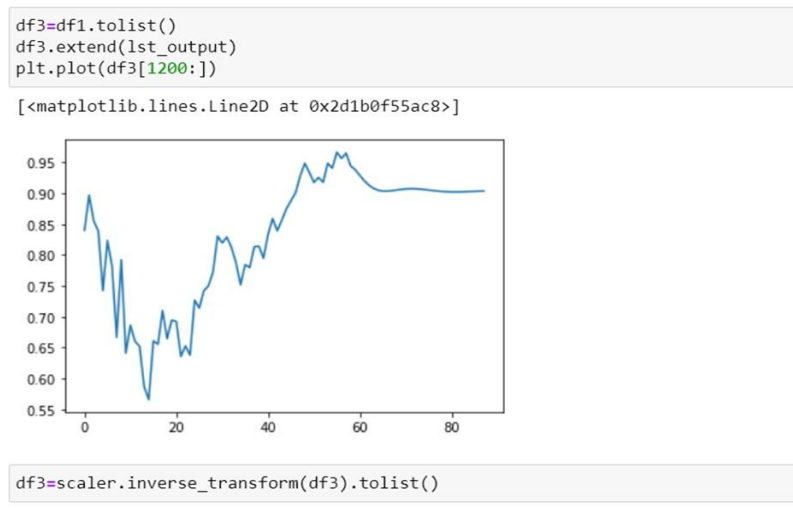


IV. RESULTS AND DISCUSSION

The result obtained after training a model using stackedLSTM is stated below:

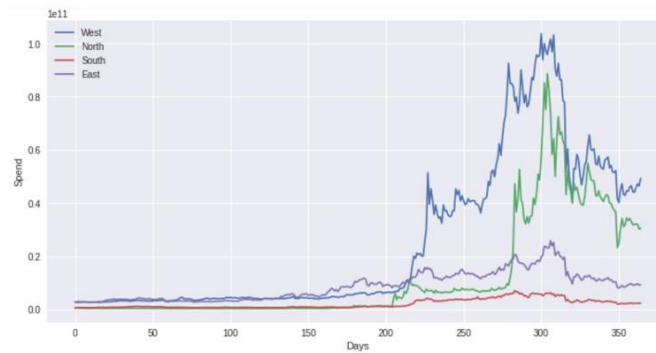


Comparison of result with the original data plotting to check the accuracy of the trained model in graphical format:



V. CONCLUSION AND FUTURE WORK

The LSTM model provides a better accuracy compared to other models as stated by different authors, LSTM model was never used in the Supply Chain Management for model creation and prediction. We have created a Stacked LSTM model. It comprises of sequential layer, LSTM and Dense Layer. The total accuracy obtained after using LSTM model is 84%. The dataset fetched was a medium sized dataset, can use big dataset to get more accurate results. The results obtained from above paper are for spend analysis, along with that we can even use predictive analysis for Demand Forecasting.



The above graph shows an analysis of spend in every zone before and after the Covid Pandemic. Days after 200 show the period when the Covid Pandemic was in better control and the days starting from 0 shows the period when the pandemic was at its peak.

Invoice List	
Invoice Types	Accuracy Obtained
Printed	92
Handwritten	84

The above table gives a proper representation of the types of invoices trained and accuracy obtained after extraction of all the possible fields from the document.

The results obtained can also be used for:

- Calculation of percentage of mode which is used the most.
- The truck which is most in demand.
- Which industry uses the system most.
- In which areas the demand of truck is the most.
- Calculation of the amount saved by the company on every order
- To predict how much the company can save for other orders based on prediction model.
- Which area has the greatest number of transporters.
- Help transporters to gain more business.

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