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A Comprehensive Study of Data Analytic Techniques for Sales Forecasting

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***Abstract* — Predicting the sales of a product or demand for a service is an utmost need in any industry. With the changes and increase in the channels and modes through which the products are sold, the prediction of sales in the future becomes tedious. The number of features that would help in predicting sales differs and increases. This leads to the usage of Machine Learning and Deep Learning Models in sales forecasting. A deep survey of various works that employ machine learning and Deep learning approaches for sales prediction is done and inferences are made. Every work studied has a list of models which are used as baseline models for comparison and the same is listed for better inferences. Works that address the problem of predicting the sales of new products are also discussed. A list of publicly available sales forecasting datasets is also given.**

Keywords—Sales forecasting, Machine Learning, Deep Learning, Time Series.

I. INTRODUCTION

The overall operations of any industry either service or product depend on the sales that they can make in the future. Hence, predicting sales will be an integral part of any system. The correctness of the sales predicted has an impact on both the internal and external processes of an organization. Any sales forecasting model should address two questions. First, the number of sales that will be made and the time in which they will be made. Sales forecasting is commonly done with the following Techniques,

- Time Series/Statistical Models
- Machine Learning Models
- Deep Learning Models

The conventional time series models [1-3] use historical sales data. But the historical data has certain drawbacks.

- Non Availability of Sufficient Historical Sales Data.
- Nonconsideration of the other factors that affect the Sales.

The former may be true in the case where new products are introduced and also when there are missing data for the existing products. The other problem is, historical sales data is not the only factor that can be used to predict future sales. Various other factors have an impact on sales. This includes basic data such as the seasonal data and leaves data in most cases and more complex data such as the features of the images which are required in the fashion industry. The models that address these issues should be capable of handling multivariate data and also possess efficient feature engineering.

These requirements are addressed by machine learning and deep learning models. The objective of this work is to study the available machine and deep learning approaches. The models studied are observed to be applied in the various datasets and the commonly available public datasets are [4-13]. This includes commonly used datasets such as the Walmart dataset, Rossman dataset, multivariate dataset as well as time series data.

The paper is organized as follows. The next section gives a comprehensive list of machine learning algorithms and the observations made from them. Similarly, the third section gives the list of deep learning approaches and the inferences made from them. The fourth section gives a summary of the inferences made. The final and fifth section gives the conclusion.

II. MACHINE LEARNING APPROACHES

[14] Applied five different regression techniques and 7 different Time Series Analysis methods in the Walmart dataset for predicting the sales. The models are implemented in the azure machine learning model. The performances of the models are compared in terms of different performance parameters and Boosted decision tree model performs than the other models. The models are used to predict the number of weekly sales. [15] Uses Rossmann Data for sales prediction. 15 features are used. As part of the features, the significance of the individual parameters is also analyzed by the users. Three different Machine Learning Models are used, LR, RF, and XGBoost. XGBoost performs well than the other two models. [16] Predicts the sales of the magazine using the Hearst Dataset. The work employs support vector regression. [17] Claims they have incorporated a better feature engineering approach for sales prediction in the Walmart dataset and applied three machine learning models. The catBoost model performs better than the linear regression and support vector regression models. [18] Uses both the time series models and the machine learning models for sales prediction in the automobile industry. The model is trained and tested with data that contains yearly, quarterly, and monthly features. The forecasting model seems to perform well in the case of monthly forecasting. Another Model that uses the Walmart dataset is [19]. It concludes that the LightBGM model performs well than a model called the prophet model which is a blended approach of time series and machine learning model.[20] uses the recursive feature elimination method for removing unwanted features and extracting only the necessary features from the Walmart dataset.

Three different machine learning Models are compared and LightBGM is found to perform well among the three models.

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[21] Have worked on individual oral care products and predicted their sales in the future using a back propagation neural network model. The comparison is made between the individual products.[22] have made a detailed exploratory data analysis of the E-Fashion Store for retrieving the appropriate features. They have compared three different machine learning models and found Gradient Boosting tree performs well. [23] Combined the XGboost and LightGBM models to create a hybrid model for detecting Walmart sales. An effective feature engineering approach is also applied which extracts features from past data. The combined model performs well than the other machine-learning approaches. In [24] in addition to making a sales forecast in general, analysis is made to identify the factor that drives high sales of medical products. Two factors, distribution channels, and marketing campaigns are considered and the corresponding sales can be predicted. Stacking of different machine learning models is used in [25] for predicting sales. Stacking helps in improving the accuracy by considering the variations in results obtained in the previous models. [26] Also uses the stacking approach and achieves better accuracy in predicting the sales of auto parts. In this case, as in various stacking processes, the dataset is split into different groups and used for training the individual models separately. The outcome of which is used at the next level. To the best observation made, [27] is the only work that uses multivariate adaptive regression splines for sales forecasting. The model is compared with the various machine learning models. In addition to predicting the sales it also clearly defines the relationship between the impacting factors and sales. [28] Uses particle swarm optimization with the various machine learning models and the Naïve Bayes algorithm is found to provide better results than other models.

Comparison is also made with the stand-alone conventional models. [29] Uses various machine-learning approaches for forecasting the sales of the components of the truck. [30] Proposes a model called the ForeXGBoost algorithm which combines the efficient missing value filling and feature extraction methods with the XGBoost model to predict the sales of passenger cars. This is the best performing model in the vehicle sales forecast competition.

[31] Combines various machine learning models to forecast drug sales. Around nine variants including the individual and combined models are experimented with and compared for better results in predicting the sales seasonally and in nonlinear trends. Holt-Winter's model is a traditional approach that is best suited for handling the trends of sales data as well as seasonal data. [32] Builds a neural network with Holt-Winter's model as its base. It roves to provide better results in predicting the sales of the wheel covers. [33] Compares various machine learning models for predicting the sales of retail stores.XGBoost algorithm along with efficient Feature Engineering is used for predicting the sales of Walmart data [34]. The model is compared with two other models and found to produce better results.

21 machine learning models are studied. The keywords used for retrieving the papers are "Sales Forecasting with Machine Learning", and "Sales prediction". The search is made in Science Direct, IEEE Xplore, and Google Scholar. The models are summarized in Table 1. The observations made are summarized below. The commonly used dataset is Walmart dataset as observed in "Fig. 1".

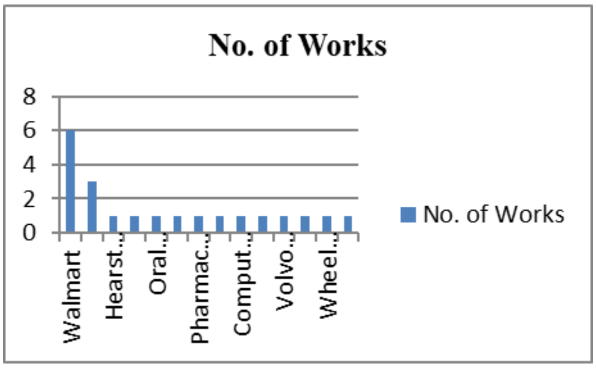

Fig. 1. Usage of Different Datasets

It has been noted from the figure that the Walmart dataset is the most commonly used and hence the results obtained with them are analyzed further. The best-performing models observed in the various works and depicted in table 1 are summarized in "Fig. 2".

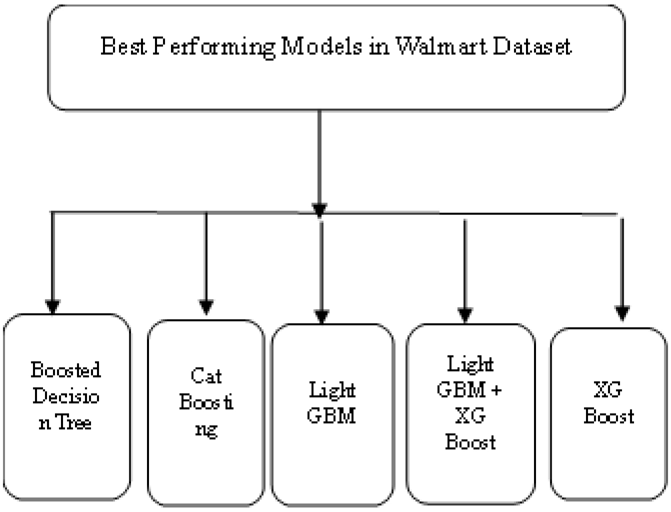

Fig. 2. Best Performing Models of Walmart Dataset

After doing cross-validation tuning across the pertinent algorithm's parameters, the comparison of five distinct methods on a test set is shown.

	Boosted Decision Tree	Cat Boosting	LightGBM	XGBoost	LightGBM + XGBoost
Retail Sales data (Walmart)	0.9614	0.9617	0.9600	0.9600	0.9623
Auto parts sales data	0.9455	0.9534	0.9453	0.9438	0.9536
Fashion store datatset	0.9826	0.9833	0.9851	0.9814	0.9856
Grocery data (Big-mart)	0.8739	0.8767	0.8732	0.8751	0.8771

Fig. 3. Cross-validation of five algorithms

When compared to the other algorithms, CatBoost Algorithm was more complicated, which meant that the

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final model almost always contained more trees and a deeper layer. The best option will be the LightGBM model if training speed is the only deciding factor.

Compared with all other combined Boosting algorithm outperforms the competition in the Retail dataset by a significant 0.8–1% margin. The discrepancies are less pronounced in the other datasets.

TABLE I. SUMMARY OF MACHINE LEARNING MODELS USED FOR SALES FORECASTING

Ref	Title	Dataset	Methods Used	Performance Parameters	Best Performing Model
14	Benchmarking of Regression and Time Series Analysis Techniques for Sales Forecasting	Walmart Dataset	**Time Series** ▪ SARIMA ▪ Non-SARIMA ▪ Seasonal Exponential Smoothing ▪ Non-Seasonal Exponential Smoothing ▪ Naïve Method ▪ Average Method ▪ Drift Method **Regression Methods** ▪ Linear Regression ▪ Bayesian Linear Regression ▪ Neural Network Regression ▪ Decision Forest Regression ▪ Boosted Decision Tree Regression	Mean Absolute Error Root Mean Square Error Coefficient of Determination	Boosted Decision Tree Regression
15	Sales Forecasting for Retail Chains	Rossmann Data	Linear Regression Random Forest XGBoost	RMPSE	XGBoost
16	Support Vector Regression for Newspaper/Magazine Sales Forecasting	Hearst Dataset	Support Vector Regression	Euclidian Distance between Actual Sales and Predicted Sales	Support Vector Regression
17	Sales Forecasting Based on CatBoost	Walmart Dataset	CatBoosting Linear Regression Support Vector Machine	RMSE	CatBoosting
18	General Sales Forecast Models for Automobile Markets and their Analysis	US-American Automobile Market	Ordinary Least Square SVM, DT, KNN, RF	MAPE	Support Vector Machine
19	Application of Machine Learning Model and Hybrid Model in Retail Sales Forecast	Walmart Dataset	Time Series Model Prophet Model LightGBM Model	RMSE	Light GBM
20	Sales Forecasting Based on LightGBM	Walmart Dataset	Logistic Regression Support Vector Machine LightGBM	RMSE	Light GBM
21	Oral-Care Goods Sales Forecasting Using Artificial Neural Network Model	Oral care products	Back Propagation Artificial Neural Networks	MAD MSE RMSE	Back Propagation Artificial Neural Networks
22	Intelligent Sales Prediction Using Machine Learning Techniques	E-Fashion Store dataset	Generalized Linear Model Decision Tree Gradient Boosted Tree	Accuracy Error Rate Precision Kappa	Gradient Boosted Tree
23	A hybrid machine learning model for sales prediction	Walmart Dataset	Linear Regression Support Vector Machine LightGBM XGBoost LightGBM + XGBoost	RMSE	LightGBM + XGBoost
24	Analysis of Drug Sales Data based on Machine Learning Methods	Pharmaceutical Sales Data	Linear Regression, RandomForest, Neural Networks Support Vector Regression Levenberg-Marquardt algorithm	MAPE MSE RMSE	Random Forest
25	Machine-Learning Models for Sales Time Series Forecasting	Rossmann Store Sales	Extra Tree, ARIMA, Random Forest, Lasso Neural Network Stacked Model	Mean Absolute Error	Stacked Model
26	Auto Parts Sales Prediction Based on Machine Learning for small data and a long replacement cycle	Auto Parts Sales	Linear Regression Support Vector Regression Stacked Model	-	Stacked Model
27	Sales forecasting for computer wholesalers: A comparison of multivariate adaptive regression splines and artificial neural networks	Computer Whole Sales	Support Vector Machine Back propagation Neural Network Cerebellar Model Articulation Controller neural network Extreme Machine Learning ARIMA Multivariate Linear Regression multivariate adaptive regression splines	RMSE MAD MAPE RMSPE	multivariate adaptive regression splines
28	A study on forecasting big mart sales using optimized data mining techniques	Grocery Data(Big Mart Dataset)	DT, RF, NB, Naive Bayes Random Forest + Particle Swarm Optimization Naïve Bayes +Particle Swarm Optimization	RMSE	Naïve Bayes + PSO
29	Forecasting Sales of Truck Components: A Machine Learning Approach	Volvo Truck Components Dataset	Support Vector Machine Regression Ridge Regression Gradient Boosting Regression Random Forest Regression	MAE RMSE	Ridge regression
30	ForeXGBoost: passenger car sales prediction based on XGBoost	Car Sales Data	Linear Regression Model Light Gradient Boosting Logistic Regression Gradient Boosting Decision Tree DT, SVM, XGBoost ForeXGBoost	logarithmic difference square root (LDSR) RMSE MAE	ForeXGBoost
31	Forecasting of sales by using a fusion of Machine Learning techniques	Rossmann	ARIMA, ARNN, SVM XGBoost ARIMA and ARNN ARIMA and XGBoost ARIMA and Support Vector Machine STL Decomposition (ARIMA, Snaive, and XGBoost)	MAE RMSE	STL Decomposition (ARIMA, Snaive, and XGBoost)
32	A Neural-Network-based Forecasting Algorithm for Retail Industry	Wheel Cover Sales Data	Holt-Winter's model Holt-Winter's model with ANN	MSE	Holt-Winter's model with ANN
33	Sales-forecasting of Retail Stores using Machine Learning Techniques	Retail Store Data	Linear Regression Polynomial Regression Lasso Regression Ridge Regression Ada Boost GradientBoost	RMSE R^2	GradientBoost
34	Walmart Sales Forecasting using XGBoost Algorithm and Feature Engineering	Walmart dataset	Logistic Regression, Ridge Regression, XGBoost	RMSSE	XGBoost

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The number of times the common machine learning models are used and tested in various studies is summarized in "Fig. 4". There are also models that are not specified in the figure but are used in a couple of works.

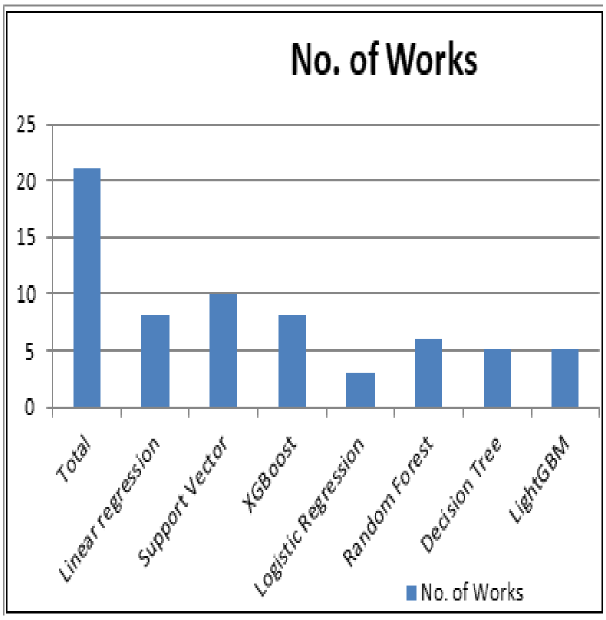

Fig. 4. Usage of Machine Learning Models

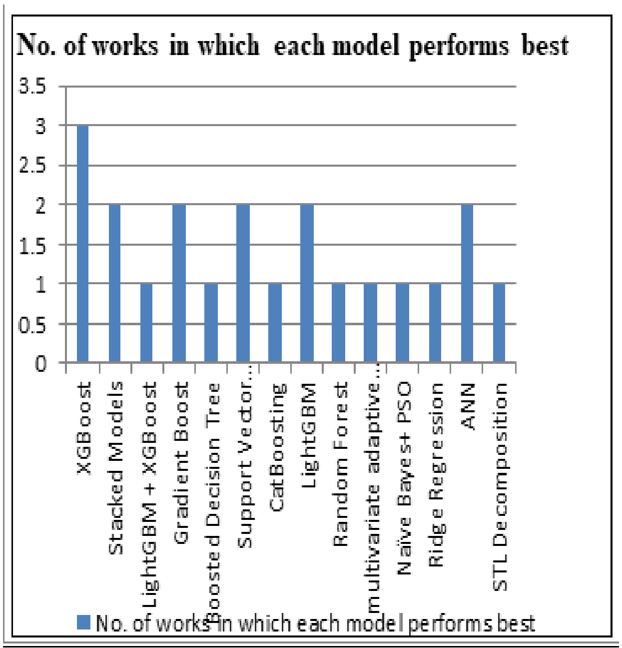

Fig. 5. No. of works in which each model performs best

The number of times a particular machine learning model performs well is given in "Fig.5." Although the datasets employed are different, this data would help in getting a general observation on the best-performed models.

III. Comparative Study of Deep Learning Models

With the trend of E-Commerce applications and the increase in the size of the data employed for forecasting, the usage of Deep Learning approaches in sales forecasting increases. TABLE II summarizes it.

TABLE II. Summary of Deep Learning Models Used for Sales Forecasting

Ref	Title	Dataset	Methods Used	Performance Parameters	Best Performing Model
35	Study on convolutional neural network and its application in data mining and sales forecasting for E-commerce	Alibaba E-Commerce Dataset.	ARIMA MBGRT PDNN CNN	MSE	CNN
36	An Aggregate Store Sales Forecasting Framework based onConvLSTM	Not Specified	ARMA ARIMA RNN CNN+LSTM	RMSE MAE MAPE	CNN+LSTM
37	Exploring the use of deep neural networks for sales forecasting in fashion retail	Fashion Retail Dataset	Decision Trees Random Forest Support Vector Regression Artificial Neural Networks Linear Regression Deep Neural Networks	R2 RMSE MAPE MAE MSE	Deep Neural Networks
38	Contribution to sales forecasting based on recurrent neural network in the context of a Moroccan company	-	RNN (LSTM) ANN RNN	RMSE	RNN(LSTM)
39	Approaching sales forecasting using recurrent neural networks and Transformers	CorporaciónFavorita Grocery Sales data	Variants of RNN and Transformers	RMSLE RMSWLE MALE	-
40	LSTM with particle Swam optimization for sales forecasting	Sales of Cars Sales of Medicines And Other Datasets	LSTM LSTM with PSO Machine Learning Models	RMSE MAE RAE RRSE	LSTM with PSO
41	Forecasting of Non-Stationary Sales Time Series Using Deep Learning	Rossmann store sales data set	Deep Learning with Trend Correction Layer	RMSE	Deep Learning with Trend Correction Layer
42	A Network-Based Transfer Learning approach to improving Sales Forecasting of New Products	Food Data	Deep Neural Network Deep Neural Network with Transfer Learning	MSE	Deep Neural Network with Transfer Learning
43	Sales Forecasting Using Deep Neural Network And SHAP techniques	Walmart Sales Data	Deep Neural Network Linear Regression Support Vector Machine	RMSE	DNN
44	Clothing Sale Forecasting by a Composite GRU–Prophet Model with an Attention Mechanism	Cloth Sales	Prophet + GRU RNN LSTM Prophet ARIMA	RMSE MAE	Prophet + GRU
45	Automatic Sales Forecasting system Based on LSTM Network	Walmart Sales Data	LSTM SVM Linear Regression	RMSSE	LSTM
46	Forecasting New Apparel Sales Using Deep Learning and Nonlinear Neural Network Regression	Fashion Retail Dataset	V3 Inception + NN	MSE RMSE MAE R^2	V3 Inception + NN
47	A Deep Learning Approach for the Prediction of Retail Store Sales	Supermarket Data From Japan	Deep Learning Approach with L1-Regularization Logistic Regression	Accuracy	Deep Learning with L1-Regularisation
48	Accurate Demand Forecasting for Retail with Deep Neural Networks	Two retail store Dataset	Structural Temporal Attention Network Ridge GRU LSVR	RSE	Structural Temporal Attention Network
49	CNN-GRU-AM for Shared Bicycles Demand Forecasting	Shared Cycle usage Dataset	LSTM GRU CNN GRU and CNN CNN +GRU +AM	RMSE MAE MAPE	CNN +GRU +AM

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Ref	Title	Dataset	Methods Used	Performance Parameters	Best Performing Model
50	A hybrid deep learning framework with CNN and Bi-directional LSTM for store item demand forecasting	Store Item Demand Forecasting Dataset	Stochastic Gradient Descent, KNN Random Forest, XGBoost Linear Regression. CNN-LSTM, CNN-BiLSTM	MAE MAPE R^2	CNN-BiLSTM
51	Forecasting pharmacy purchases orders	Pharmacy Purchase Dataset	SARIMA Prophet LR, RF, LSTM	Accuracy	SARIMA
52	Retail Demand Forecasting: a Comparison between Deep Neural Network and Gradient Boosting Method for Univariate Time Series	German Retail Store Data	Deep Neural Network Gradient Boosting	MAE RMSE	Deep Neural Network
53	Retail Demand Forecasting using CNN-LSTM Model	Data from 10 Stores	MLP, LSTM, CNN CNN+LSTM	RMSE	CNN + LSTM
54	Forecasting of Sales Based on Long Short Term Memory Algorithm with Hyperparameter	Sales Data	LSTM	RMSE	LSTM
55	A Sales Prediction Method Based on LSTM with Hyper-Parameter Search	Rossman data	Machine Learning Models LSTM LSTM with Hyperparameter Search	RMSPE MAPE	LSTM with Hyperparameter Search
56	Future Sales Prediction For Indian Products Using Convolutional Neural Network-Long Short-Term Memory	Bigmart Dataset	CNN +LSTM	Precision	CNN+ LSTM

[35] uses the capability of the convolutional neural networks to extract the features effectively from the available dataset and predict the sales forecast. [36] Uses a novel model that combines the convolutional neural networks and LSTM. It differs from the other works in the way that it also considers the sales data of the neighboring stores along with the sales data of the considered store. The combined model is compared with the other statistical model and the individual RNN model and the combined model perform well. [37] Designed a deep neural network model for forecasting sales in the fashion retail market. The preprocessing includes various aspects such as the aspects of the company and the domain expert's decision. The deep neural network model performs well than the other machine learning models. [38] Have tested various variants of the recurrent neural network model for forecasting sales. RNN with LSTM is found to perform well when compared with conventional artificial neural networks and RNN.[39] have developed a model for predicting sales at three different levels, Item, day, and store levels. It employs RNN and Transformers and also introduced the concept that using dynamic time for learning to avoid overfitting. [40] Uses particle swarm optimization for selecting the features from the sales dataset and LSTM for Training and Sales Prediction. The approach is tested with different datasets and compared with different machine learning models. [41] Introduces a layer for correcting the trend with the help of the predicted sales value and the weight value. This results in better accuracy. To address the problem of forecasting the sales of the newly introduced data, [42] introduces the transfer learning approach in deep neural networks.

The model is trained with the existing products and used for predicting the sales of the new products. [43] Designed a deep neural network model for forecasting the sales of Walmart data. An effective visualization mechanism is also used for enhancing the model. The deep neural network performs well than the linear regression model and support vector machine. [44] Combines the prophet model with the gated recurrent unit for predicting the Sales of the clothes. The combined model performs well than the other individual deep-learning approaches and Time series Models.

[45] Uses LSTM with hyperparameters tuned with search grid optimization for predicting Walmart sales. Since the sales of the products like fashion clothes depend on the style and other similar attributes, [46] uses image features as parameters along with sales history data for predicting future sales.

A variant of the CNN model is used for feature extraction and a neural network is used for prediction. [47] Uses a deep learning approach with L1 regularization for predicting the sales of the supermarket data. [48] Proposed a model which combines the concepts of gated recurrent unit, Auto regression, and Attention models to create a prediction model which takes into consideration the structural and temporal details of the products and the relation between them. [49] Also uses multiple deep learning approaches for predicting the sales, CNN for extracting the Features, Gated recurrent unit, and attention mechanism for finding the relations at the consecutive levels. This is used in the service industry for forecasting the demand for shared bicycles. While most of the works combine CNN with LSTM, [50] combines CNN with Bi-LSTM for predicting the demand for store items. The model is found to perform well than the CNN-LSTM and other machine learning algorithms. [51] Has been the only work that predicts the demand for Pharmacy products. Prediction of the weekly demand and daily demand is made and it is observed that the former performs well than the latter model.

When most of the works use multivariate data for forecasting [52] and compare the performance of the deep neural networks and Gradient Boosting algorithm in predicting the sales with the univariate data. [53] Combines CNN with LSTM for predicting the sales data of different stores. A new activation function called the Swish activation function is employed which results in better performance. [54] Tested LSTM for predicting sales. The work compared various LSTM models that are differentiated by the number of hidden layers, number of epochs, size of the batch, etc.[55] also uses hyperparameter tuning in LSTM for making a better prediction. [56] Combines convolutional neural network and long short-term memory for predicting the sales of the big mart dataset. Both historical sales data and time series data are used.

The following are inferred from the study made with the deep learning works. The commonly used model is LSTM. LSTM is used in combination with other models for better performance. As a surprise in a specific case of predicting the sales of the pharmacy products, the conventional SARIMA performs better than the Deep learning models. As stated earlier, with the increased usage of e-commerce sites, the decision of the users to buy a product depends on the characteristics of the products as in the case of fashion products, Deep learning models are useful. Consider an e-commerce site that sells apparel, the buying decision may depend on the color and style. Such parameters should also be considered for sales prediction. This demands a mechanism to extract features efficiently. CNN plays the role. The such basic architecture is shown in "Fig. 6".

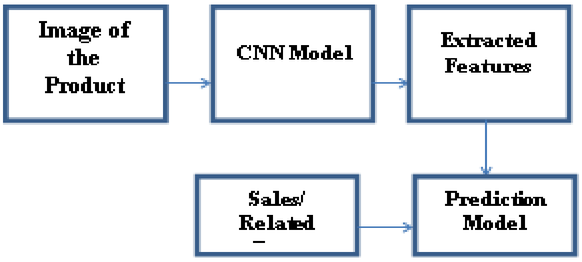

Fig.6. Basic Architecture of Feature Extraction and Prediction

Another Key problem is the prediction of sales of the new products. This is solved by the concept of Transfer Learning. The features learned from the previously existing products are applied to the new similar products. The basic architecture is shown in "Fig. 7".

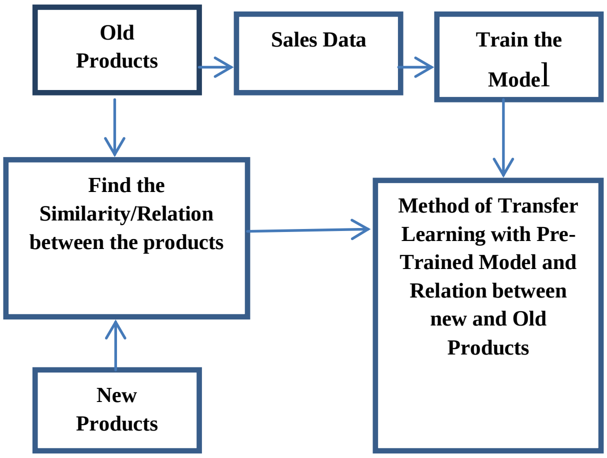

Fig. 7. Architecture of Transfer Learning approach

When the transfer learning approaches are studied, it has also been noted that it is not the only approach to handling new products. Earlier, combined models [57,58] which use clustering for identifying the relationship between the products and regression for prediction are used for addressing this issue.

With the introduction of e-commerce sites, another parameter called the reviews from the users has also gotten attention in predicting sales. Every product displayed on the e-commerce site is reviewed and commented on by the buyers. It could be either positive reviews or negative reviews. The important part of the process is to identify the sentiment of the review as either positive or negative. Although many works have used this approach[59-64], these works are not in the scope of this work.

IV. Inferences

The following inferences are made from the above-discussed works.

- In the case of machine learning models, XGBoost performs well than the other models in a few works.
- The usage of stacked models increases the performance
- In predicting the sales of new products, clustering is combined with regression models to achieve better performance
- In the case of the deep learning approaches, LSTM plays a key role in making predictions.
- Deep Learning approaches address the problem of predicting the sales of new products with the Transfer learning approach
- In the case where the image features are also included as the parameter for sales prediction, Convolutional neural network models are used for feature extraction.

V. Conclusion

State of art machine learning and deep learning approaches are studied. Problems with the time series data and models are stated. The need for machine learning models and deep learning models in sales forecasting is also discussed. The commonly used datasets and the best-performing model in each of the datasets are given. The changes that have occurred in the sales of the products and the resulting needs to be incurred in the sales prediction approaches are also discussed. The available solutions for them are also illustrated.

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