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Effective Demand Forecasting Model Using Business Intelligence Empowered With Machine Learning

MUHAMMAD ADNAN KHAN[1], SHAZIA SAQIB[1], (Member, IEEE), TAHIR ALYAS[1], (Member, IEEE), ANEES UR REHMAN[1,2], YOUSAF SAEED[3], ASIM ZEB[4], MAHDI ZAREEI[5], (Member, IEEE), AND EHAB MAHMOUD MOHAMED[6,7], (Member, IEEE)

[1]Department of Computer Science, Lahore Garrison University, Lahore 54000, Pakistan
[2]Systems Limited Pakistan, Lahore 54000, Pakistan
[3]Department of Information Technology, University of Haripur, Khyber Pakhtunkhwa 22620, Pakistan
[4]Department of Computer Science, Abbottabad University of Science and Technology, Khyber Pakhtunkhwa 22500, Pakistan
[5]Escuela de Ingeniería y Ciencias, Tecnológico de Monterrey, Zapopan 45138, Mexico
[6]Electrical Engineering Department, College of Engineering, Prince Sattam Bin Abdulaziz University, Wadi Addwasir 11991, Saudi Arabia
[7]Electrical Engineering Department, Faculty of Engineering, Aswan University, Aswan 81542, Egypt

Corresponding author: Mahdi Zareei (m.zareei@ieee.org)

ABSTRACT In the modern era business intelligence (BI) has a pivotal role in articulating a strategy and taking correct measures based on data. Business intelligence plays a pivotal role in an inevitable decision support system that enables the enterprise to perform analysis on data and throughout the process of business. Machine learning predicts the forecasting of future demands of the enterprises. Demand forecasting is one of the main decision-making tasks of enterprise. For demand forecasting first raw sales data is collected from the market, then according to data, the future sale/product demands are forecasted. This prediction is based on collected data that compiles through different sources. The machine learning engine executes data from different modules and determines the weekly, monthly, and quarterly demands of goods/commodities. In demand forecasting, its perfect accuracy is non-compromising, the more accurate system model is more efficient. Furthermore, we test the efficiency by comparing the predicted data with actual data and determine the percentage error. Simulation results show that after applying the purposed solution on real-time organization data, we get up to 92.38 % accuracies for the store in terms of intelligent demand forecasting.

INDEX TERMS Business intelligence, demand forecasting, prediction, machine learning, AWS sage maker, sale forecasting.

I. INTRODUCTION

In this era of technological advancement, business intelligence plays a pivotal role in decision aspects of the company related to future endeavors. Business intelligence (BI) termed as the methods technique and concepts having a positive impact on the decision for business by excursing the support of fact-based systems. It is the architecture and technology that transforms raw and disparate data into meaningful full informative data. This informative data assists in establishing new strategies, enable operational excellence, tactical insights, and firm decision making for future aspects of the company.

Business Intelligence (BI) is set up to play a decisive role in almost all kinds of business in the modern era and in the near future. Business Intelligence (BI) is inevitable for analytics and strong decision making for all sorts of businesses ranging up to all sectors. It is not only improving the efficiency and effectiveness of enterprise organizations, but it also reduces the cost and losses. It helps in retaining and attracting the customer, improving sales, and many other significant benefits. Business Intelligence (BI) predicts the future trends of the market. Machine Learning is used as one tool and technology another tool to implement a business intelligence (BI) concept using demand forecasting for a particular business.

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Demand forecasting is the branch of predictive analytics [2] and become famous over time. There are traditionally two basic assessment methods used in demand forecasting. One is Qualitative assessment [3] and the other one is Quantitative assessment [4]. With time as research increases, these methods are enlarged in further types and some other methods forecasting ideas and combinations were introduced.

Demand forecasting is the estimated requirement of products/services in the future on the bases of present and past data and different aspects of the market. As all organization faces the unknown future and we don't know in future product demand. Thus, by analyzing past data and current market data, we may predict the future demand and manufacture those goods whose more demanding in the near future. Consequently, we may produce the required products according to the demand of the market in advance. This will also determine the potential buyers to the company/production facility, besides the products that the company needs to manufacture [1]. Eventually, the right prediction may lead to the earning of the company. In other words, demand forecasting is an essential addition in efficient and effective management planning. In developed countries where industrially demand requirement is uncertain demand forecasting is also beneficial to them.

The remainder of this paper is organized as follows. Section II briefly describes the Literature Review. Section III presents the proposed system method in which carries out a comprehensive evaluation for Business Intelligence of Effective Demand Forecasting as output. Section IV discusses the simulation and results of the proposed model. Sections V discusses the conclusions from the study.

II. LITERATURE REVIEW

Different studies conducting on-demand forecasting models predicted sales calculated using Machine Learning (ML) regression models and methods with time series analysis for forecasting sales numbers using extended features. Azure Machine learning platform is used for that. Different regression techniques were applied to get a specific result [5].

The fuzzy-neural network [6] implemented for sales forecasting and demonstrated that this model's performance is better than traditional neural networks. An approach named Gray extreme machine learning with the Taguchi method [7] which demonstrates better system performance than the performance of artificial neural networks. Forecasting for month electricity sales purposed in china [8] uses clustering, regression, and time series analysis techniques. Time series analysis auto sales [9] also carried out in China. The periodic effects were calculated by using the exponential weighted moving average. After that, considered effects and the calculated frequency are merged for the linear regression technique. ARMIMA and neural networks are combined for forecasting [10]. Cloud computing-based forecasting [11] system and applied time series analysis with the moving average method are also implemented for forecasting. Systems are installed on Azure cloud, used PHP programming language and MySQL database. Moving average methods are being implemented to forecast the sales for a long time in the literature [12]. A forecasting engine based on genetic algorithm also embedded [13].

A customer model [14] created a which uses customer-browsing behavior and verified the model on an e-commerce website. Another technique the merger of the SARIMA and wavelet transform method for forecasting. A hybrid model is demonstrated that delivers better performance than the single methods [15].

A hybrid model is designed as a hybrid model, which combines k-means clustering and fuzzy neural network for the prediction of circuit boards [16].

A model purposed which uses extreme learning machine and harmony search algorithm for prediction of retail supply chains and displayed that the new model provides better performance than the ARIMA models [17]. A fuzzy logic and Naïve Bayes classifier also used for forecasting [18]. Recurrent Neural Networks also implemented to forecast sales [19]. An extreme Machine Learning (ML) algorithm is used for prediction [20]. The Back Propagation Neural Network for forecasting is also implemented [21]. A hybrid method introduced based on MARS and SVR techniques for the prediction of IT products. They established that the new model provides better performance than the single SVR [22]. Numerous features such as fuel price, holiday, unemployment, temperature, store, and date are applied to forecast the weekly demand in Walmart and showed that Support Vector Machine delivers the best performance [23].

Forecasting was used in many fields and areas, as technology upgraded, we combine this field of the area with technology and nowadays Machine learning, Artificial Intelligence, Data Science play an important part.

The system discussed in this paper is to forecast future sale products. The distinction between classification accuracy and forecasting accuracy is important and some-times unappreciated [24]. For accuracy, we need accurate past and present data, for accurate estimation. In any case, if our collection of market data or lack of market person statement, we may miss our past data accuracy, and as a result, the prediction may be wrong which causes the forfeiture in business. We can compare our forecast data with real-time data and find the percentage of perfection and erroneous.

Systems under discussion consist of different modules in which we run our collected data. The output result is an indifferent format that encompasses weekly, monthly, and quarterly, yearly. We should import the sale data file in the system and execute it, after some time when data is compiled by the system, it shows the demand forecasting for next year based on the provided data. We can manually edit the data or can enter the current week data. This system is primarily helpful for decision-makers to improve its business and stopover to produce unwanted products in the market.

Despite having a renowned ERP system and a bunch of custom applications, the company lacks Proper forecasting rules and/or AI-based forecasting to establish future forecast

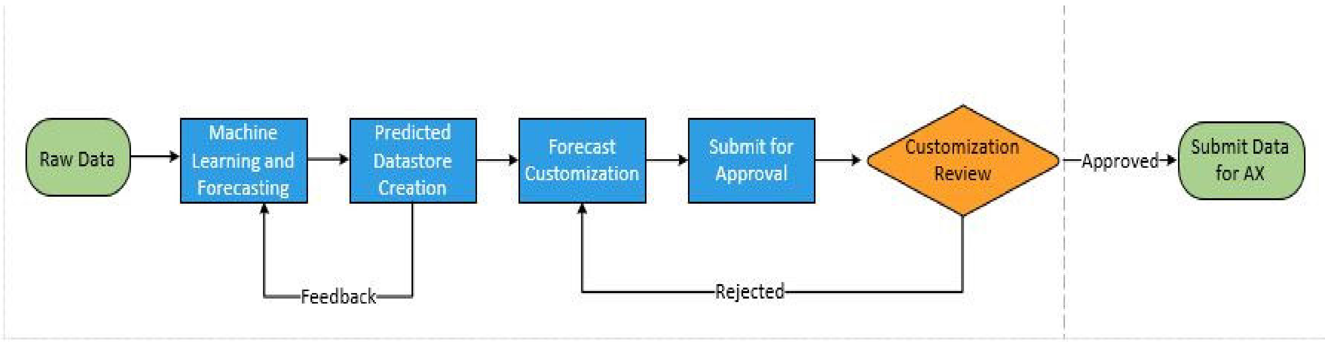

FIGURE 1. A high-level overview of the proposed system.

numbers. a central application to encapsulate all the processes and Knowledge and information sharing within the department, rather limited to individuals.

The Company's previous systems were excel based for forecasting that is causing trouble in various ways

- Non-centralized control.
- Poor visibility to stakeholders.
- Change Control.
- Approval Mechanism.
- Change tracking and history.
- A system relies on individuals.

III. PURPOSED SYSTEM

Now let's discuss the purposed system in complete detail. The components in the purposed model and their interaction. Figure 1 shows the high-level overview of the proposed system and Figure 2, 3 & 4 shows the detailed interaction of each component. How every component proceeds. Let's discuss this in detail.

Machine learning-based forecasting systems introduced to overcome the above hindrances. As shown in Figure 1 the system gets data from different sources to provide raw data to the Machine learning model.

Model and Rule engine provides a forecast based on historical data. Forecasted values dumped in the database and used in front end application for processing. Front end application shows predicted data for the store every week then that data was aggregated to higher levels of hierarchy based on rules laid down by business. Front end application has the functionality to alter the numbers and approval workflow process in place. After alteration and approval data submitted to AX for further strategic decisions of sales and inventory.

A. DATA SOURCE

Data is the most important part of any BI centric application or model. Purposed model acquires data from different sources i.e sales inventory and calendar, as shown in Figure 2.

Data will be generated from these sources for forecasting, primary sources of data are sales, inventory, and calendar. Calendar acts as a metadata /timeline for time series based on

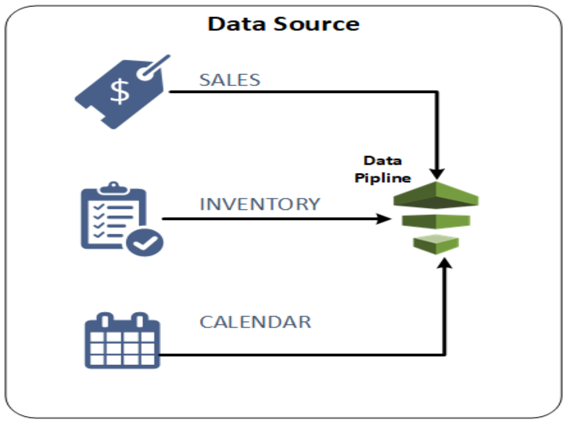

FIGURE 2. Detailed overview of system data source.

fiscal years. Sales and inventory data are based on previous years of actual data. Data from 2014 onwards is used for predictions.

The data generated is the real-time data of an organization. The inputs used for the purposed model are as follows, historic sales data of year, Calendar of year, holidays for sales spike, data from a marketing perspective includes discounted/promotional days. Input to model also includes historic share and contribution on each shop in with sector and subsector.

Data is dumped into the common database from all different sources. Data cleansing is performed before it processes and considered for the next stage. Data cleansing and preparation for Machine Learning (ML) input.

The grain of the data is shops * weeks as that is also the grain of perdition from ML. Data dumped is shopping wisely as the purposed system predicts the next 52/53-week sales shop wisely. So, all three data sources are important for forecasting. Data refinement activity is performed before pushing it to AWS S3 Storage.

B. MACHINE LEARNING

Business Intelligence (BI) forecasting model using machine learning (ML) provides vital support in decision making. Purposed model for (ML) part takes data input from the

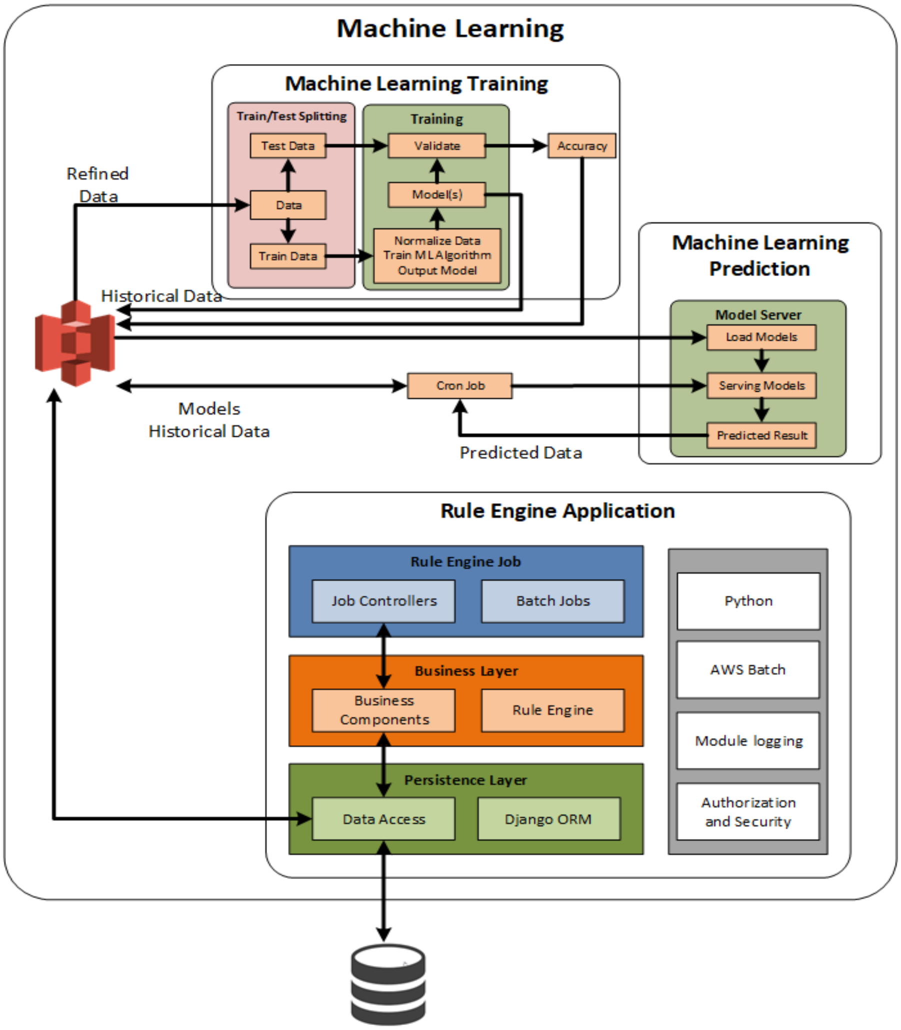

FIGURE 3. **Detailed overview of system Machine Learning Model and Rule Engine.**

data source, refined and preprocess the data. Refined and preprocess data used as input to the machine learning training model as shown in figure 3. The training model results and accuracy stored in data sources. these trained models are used for data prediction. The rule engine is also applied where we have shops with less data then it is used in combination with ML predicted model.

Figure 5 shows the working cycle of how Machine Learning engine works. First three steps are involved for in preprocessing of data that includes data fetching (Data from repositories that are stored in processed form from different sources) cleansing (That cleansing is with performed on processed data from data sources to improve the training results) and preparing before the model training then training evolution of models and then deployment plus monitoring

In this phase of system Machine Learning (ML) activities carried out. Machine Learning engine splits the data into further categories i.e. training and testing data. Data normalization activity carried out on training data.

Before jump into model training, data under discussion is explored analyzed and preprocess according to needs, for example, let's consider a famous data MNIST before training started on this data set, the data is transformed in a way that it gives the best result and training efficiently. To preprocess a data following method has been used.

- Jupyter notebook on amazon sage maker notebook instance. The notebook has been used for some other purposes
  - Code is written for job training model
  - Model deployment on amazon sage maker hosting
  - Testing and validation of models

On that normalized data, the Machine learning algorithm is trained. Machine Learning (ML) algorithm is trained using the hyperparameters extracted from the fiscal calendar (fiscal week, fiscal year, holiday calendar) as prediction will be based on a fiscal calendar with other sales factor of stores. Training of model is based time series. Machine Learning algorithm generates models based on the normalized data and

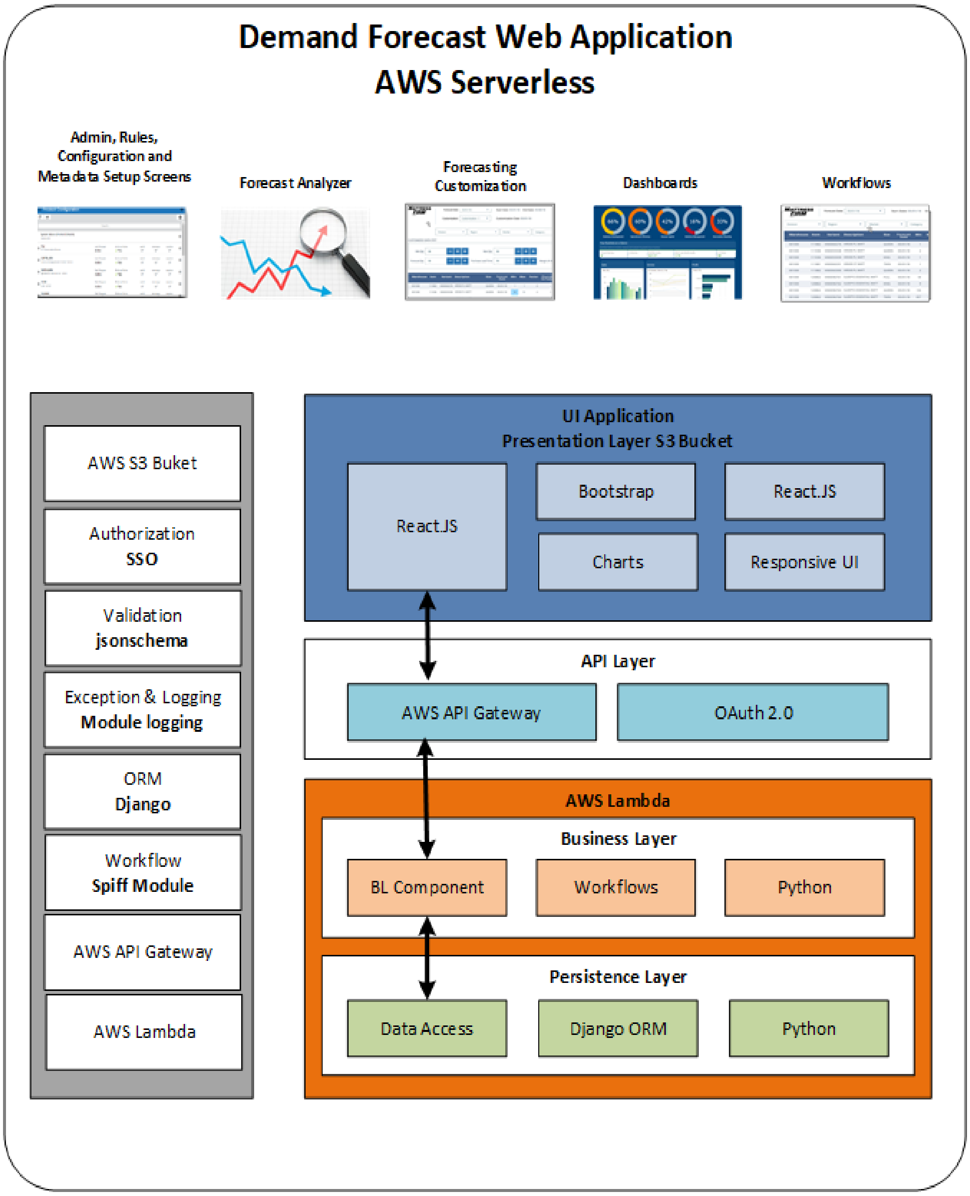

FIGURE 4. **Detailed overview of the system We Architecture.**

hyperparameters (These are deduced from input data). These models are then validated on test data. After model validation accuracy of the models is calculated and stored in the AWS S3 bucket.

The system under discussion tweaks hyperparameters according to the requirement of time series and the company's business. Hyperparameters have a great impact on resultant models. One training data set and optional test dataset is accepted by Deep AR during training. A test dataset had been used to evaluate the trained dataset.

In the next phase Machine Learning (ML) prediction is carried out. Machine learning models will serve as input and provides the desired prediction. Machine learning predicts the sale of each store week wise. The machine-learning algorithm predicts sales based on time series. The algorithm used for forecasting is a supervised learning algorithm for one dimensional (scalar) time series using Recurrent Neural Networks (RNN). The amazon sage maker Deep AR algorithm has been used for this time series prediction. Amazon sage maker is referred to as a fully managed machine learning service.

Generally, time-series don't have to be the same for both train and test datasets. The preference is given to Deep AR ahead other time series algorithms because Deep AR outperforms others when it comes to hundreds of time series.

These predicted results by supervised learning algorithms are then stores in the AWS S3 bucket. Some of the predictions carried out based on some rules these rules are applied to stores that will be open soon or open just recently. For those

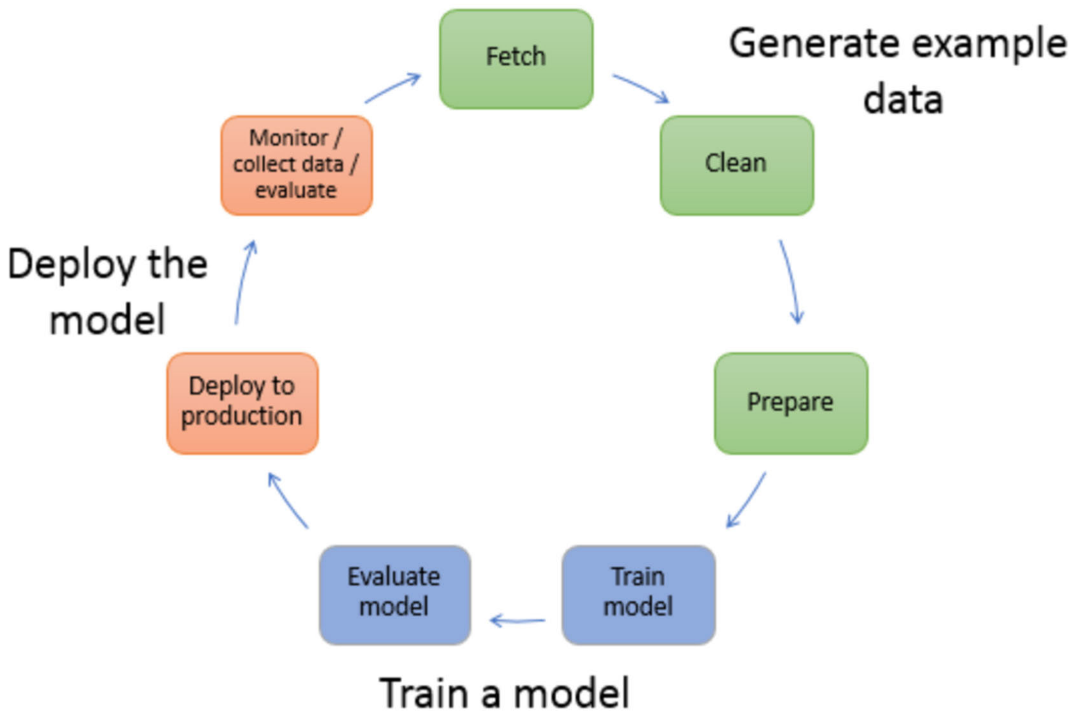

FIGURE 5. Machine Learning (AWS) implementation cycle [25].

stores, Rule engines provide a prediction based on rules and factors affecting sales in particular. These factors might be sales holiday's bonus cards etc.

The company has complete hierarchy levels i.e. shops belong to a particular sub-sector, sub-sector belongs to a particular sector, and sector belongs to a particular area. That shop prediction is then crunched to make the sales of sub-sector and areas.

The system publishes forecast every week and 52 weeks forecast published ranging from a current fiscal week to the next 52 weeks. Weeks can be from the current fiscal year or next fiscal year depending upon the publishes week of the forecast.

C. SALES/INVENTORY FORECAST WEB APPLICATION

Once all these prediction results are dumped into a database. Front end application built in Angular uses ASP.net Core

Restful web services as backend come into action. Figure 4 shows a detailed overview of the architecture used for the application. Figure 6 describes the client-side architecture implemented using angular and angular material.

The app fetches the predicted results from the database and arranges the data shop * week format. After that higher hierarchy aggregations are carried out on shop*week data.

Data is aggregated on a monthly and quarterly bases. Which gives a complete forecasted picture.

The functionality has been exposed to the user to adjust the predicted numbers, this is additional functionality that provides more control to the user and company. The web-based application gives flexibility to end-user for:

TABLE 1. Shop 1 (North sector) comparison of actual and forecasted for December 2019 Weeks.

Shop#	Week#	Actual	Predicted	Accuracy
Shop 1 (North Sector)	Week1	4925	5500	88.32%
	Week2	3621	3050	85.75%
	Week3	5413	6278	84.01%
	Week4	13985	15623	89.71%

- ML numbers crunching.
- Mass updates to store or product grouping numbers.
- Thresholds to review changes impact.
- Approval workflow process.

D. DYNAMICS AX

Based on approval from web app data has been passed on to dynamic AX where the decisions and planning takes place for the future. Using these data orders are placed for the purchase of relative items.

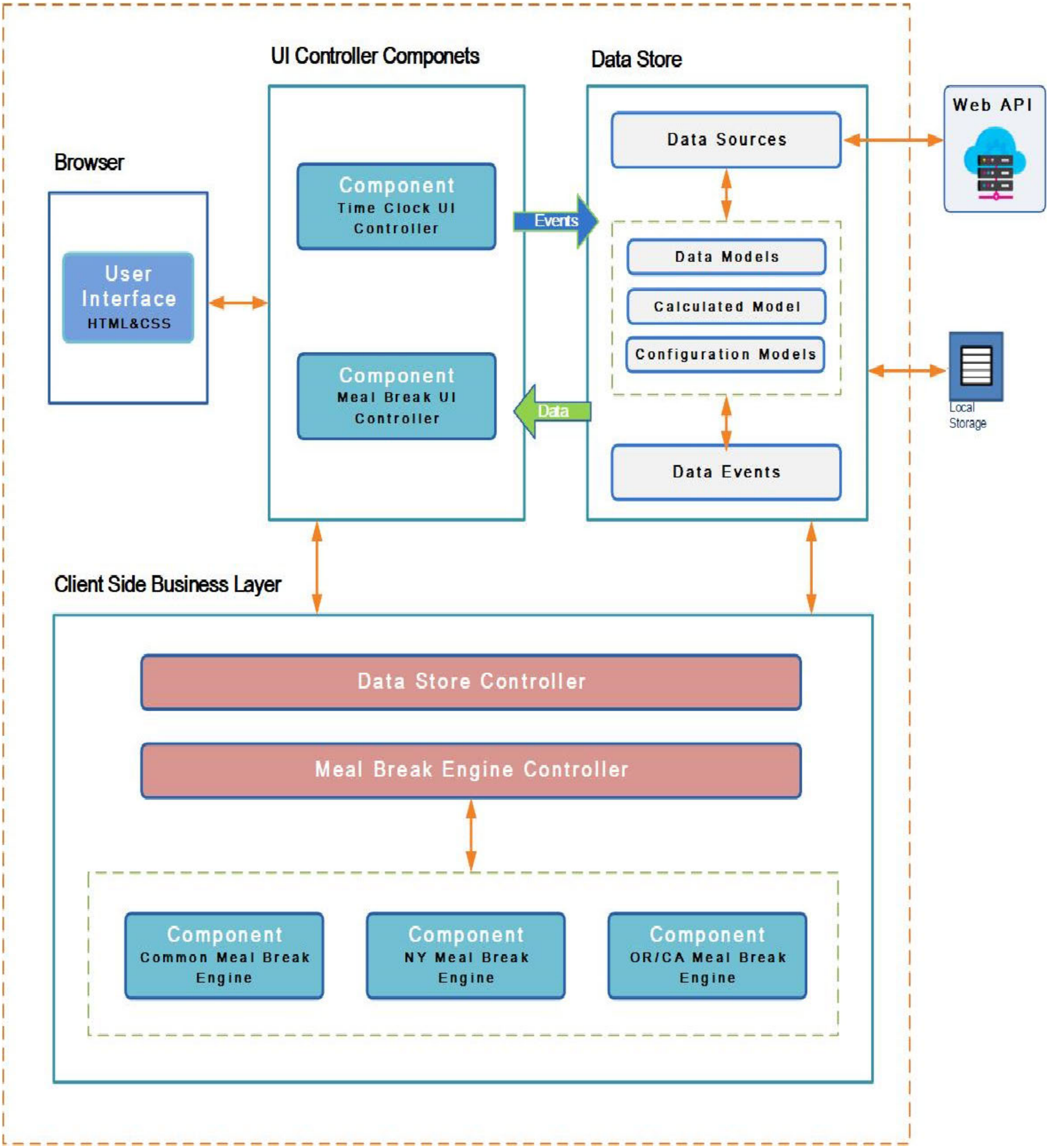

FIGURE 6. Web application architecture builds on Angular / Angular material.

IV. SIMULATION RESULTS

For forecasting the sales and inventory historic data has been analyzed. After the cleansing of historic data from 2015 onwards hyperparameters are fine-tuned to get the maximum forecasting results. Table 1, 2 and 3 shows week wise actual and predicted results for December 2019.

Table 1 shows the predicted and actual results of shop 1 in the north sector. The perdition for December is very effective as compared to the previous system where accuracy is around 50% as it is a manual process based on excel formula. As we have a fair amount of historic data which helps in predicting with great accuracy. The prediction varies from week to week or month to month as systems give accuracy with under perdition and over prediction.

Table 2 shows the accuracy of newly opened shops that do not have much sales and inventory history. We have use

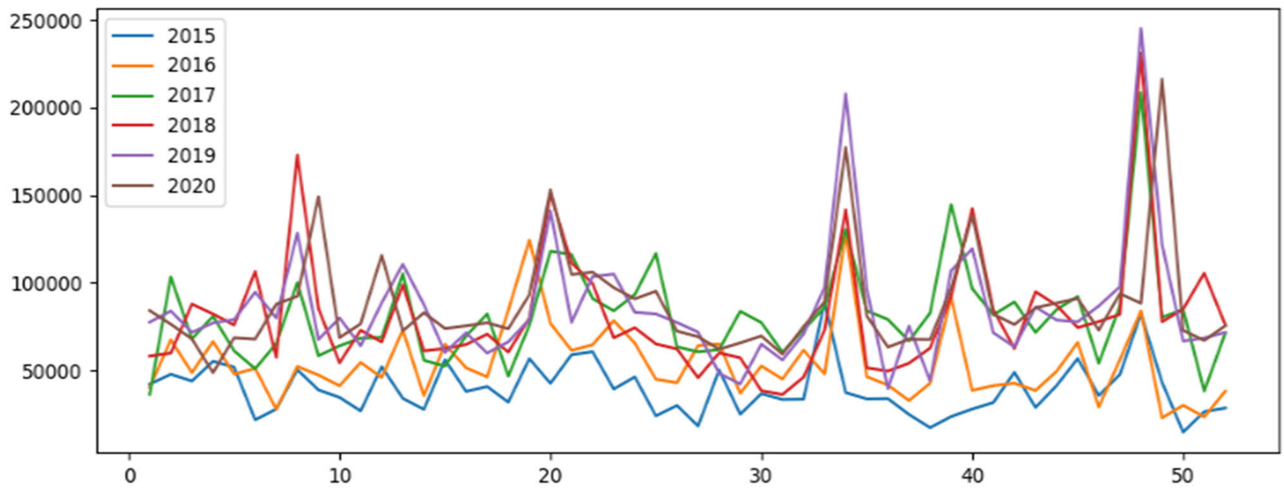

FIGURE 7. The graph shows historical data of and future year 2020 prediction. The X-axis shows weeks and the y-axis shows sales/ inventory is converted in dollar $. This is a representation of the north sector.

TABLE 2. Shop 12 (East Sector) comparison of actual and forecasted for December 2019 Weeks.

Shop#	Week#	Actual	Predicted	Accuracy
Shop 12 (East Sector)	Week1	5175	6521	73.99%
	Week2	3621	2821	77.99%
	Week3	6430	5120	79.62%
	Week4	9652	12250	73.08%

TABLE 3. Shop 2 (East Sector) comparison of actual and forecasted for December 2019 Weeks.

Shop#	Week #	Actual	Predicted	Accuracy
Shop 5 (East Sector)	Week1	6621	7125	92.38%
	Week2	10253	8854	86.33%
	Week3	9851	11321	85.07%
	Week4	14232	15587	90.47%

rule-based with machine learning prediction for shops of such a kind. As historic data grows for such shops Machine Learning (ML) prediction algorithm (Deep AR) will output better results based on time series and hyperparameters.

Table 3 shows the data of shop 5 of the eastern sector as we have a fair amount of historic data with good hyperparameters, the perdition results are excellent with over 90 % in this sector and sub-sector.

A. GRAPHICAL REPRESENTATION SECTOR WISE

Results are compiled sector-wise to show data graphically sector-wise as shown in Figure 7, Figure 8, Figure 9. Historic data have been mapped with the future year perdition as a model provides a prediction of 52/53 weeks of a complete fiscal year. The results are shown on the higher hierarchy as our front-end app shows the data based on hierarch levels, starting from shops to sub-sectors, sectors up to the highest level. For simulation, python is used with the Jupiter notebook.

Figure 7 represents the data spikes of a complete north sector where historic data has been considered from 2015-2019 and the year 2020 is predicted based on historical data. Data spikes show considerable good results that strengthen the fact that prediction will be accurate and near to reality as historic data improves.

Figure 8 represents the data spikes of a complete west sector where historic data has been considered from 2015-2019 and the year 2020 is predicted based on historical data.

Figure 9 represents the data spikes of the complete south sector where historic data has been considered from 2015-2019 and the year 2020 is predicted based on historical data. Data spike shows the accuracy of the predicted model.

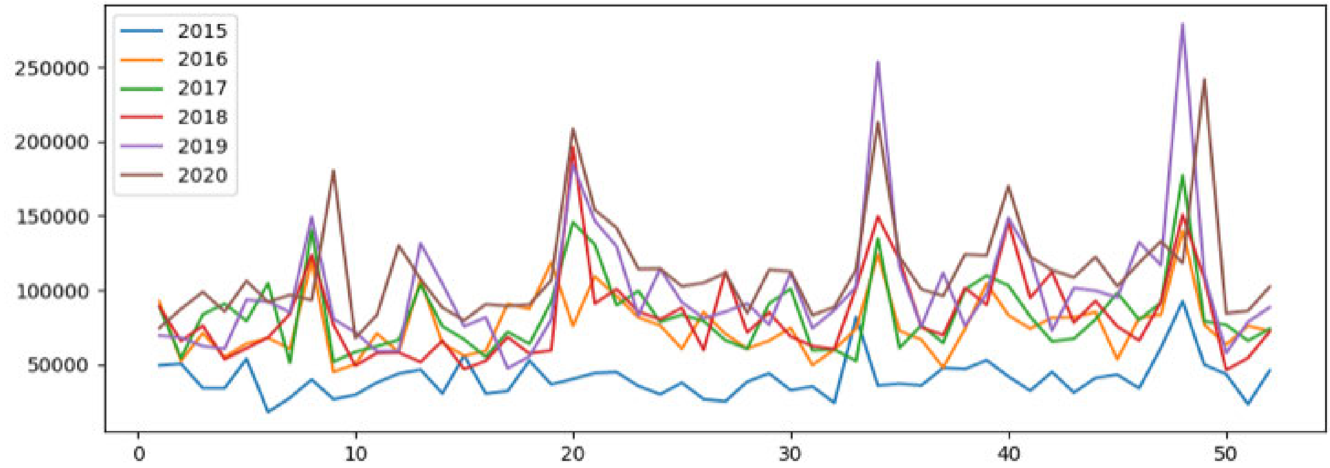

FIGURE 8. The graph shows historical data of and future year 2020 prediction. The X-axis shows weeks and the y-axis shows sales/ inventory is converted in dollar $. This is a representation of the west sect.

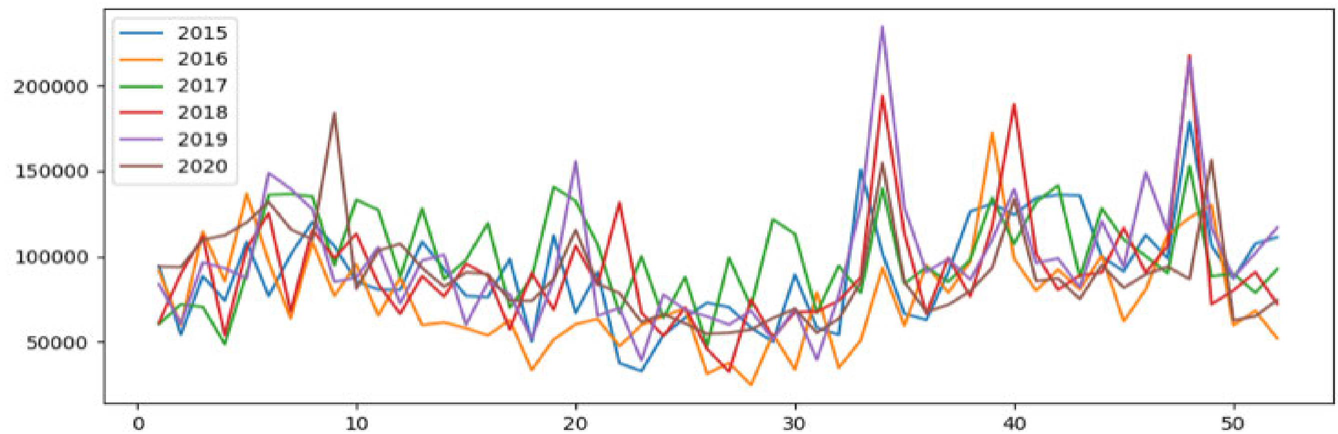

FIGURE 9. The graph shows historical data of and future year 2020 prediction. The X-axis shows weeks and the y-axis shows sales/ inventory is converted in dollar $. This is a representation of the south sector.

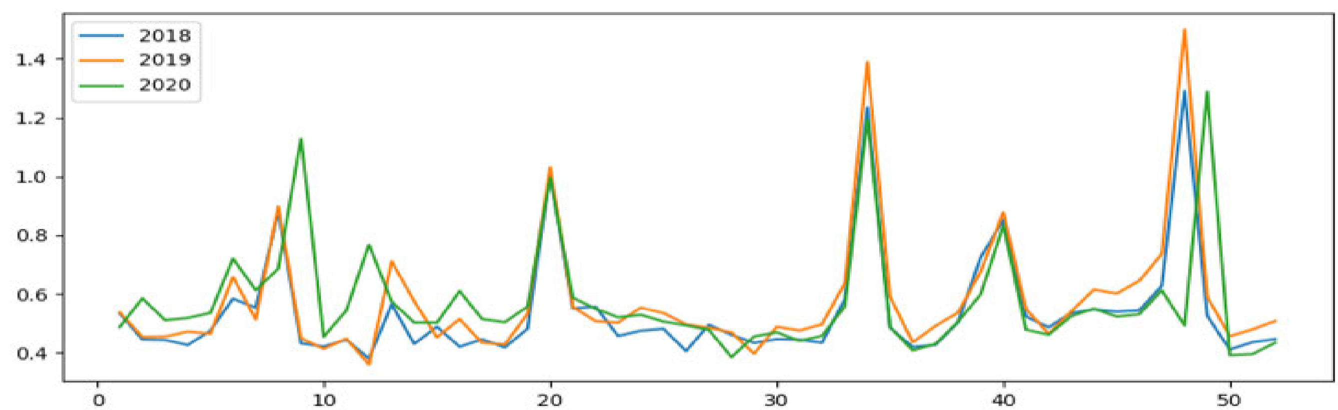

FIGURE 10. The graph shows historical data of and future year 2020 prediction. The X-axis shows weeks and the y-axis shows sales/ inventory is converted in dollar $. This is a representation of the overall organization.

Figure 10 shows the graph of the overall organization. The plotted graph is of 2 historic years and one forecasted / predicted year. This simulation provides better results as over historic data grows that already shown that the increased historic data provides better results.

V. CONCLUSION

As the modern era is the era of technological advancements.

Business intelligence (BI) practices are also the need of the hour. As business intelligence (BI) practices are applied throughout the enterprise, these practices lead to accurate and effective decision support. BI helps in stabilizing the business, make it more sustainable, and increase productivity.

For enterprises, the importance of demand forecast doubles as the day passes. Previously organizations do these calculations manually or some irrational techniques were there.

As the market is becoming more dynamic and robust the forecasting has not only changed the organizational philosophy of the business and culture of an organization, it also increases executive support, cooperation, and transparency significantly.

In this system, the demand forecasting enhances the operational productivity reduces the losses and wastages, as the company doesn't have the production Units they purchased items based on forecasting.

High forecast accuracy helps in formulating established market strategy, stock turn over increase, decrease in supply chain cost, and an increase in customer satisfaction.

In this study effectiveness of time series and rule-base forecasting has been analyzed. As per forecasting calculations, the performance of DeepAR models is highly accurate and comparative. This concludes the percentage error values are relatively small so DeepAR models give a high percentage on accuracy for forecasting. As data size grows the model produces more accurate results.

Depending upon accuracy new study can be related to stock optimization. So, the stock/product optimization point can be a new starting point.

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MUHAMMAD ADNAN KHAN received the B.S. and M.Phil. degrees from International Islamic University, Islamabad, Pakistan, and the Ph.D. degree from ISRA University, Pakistan. He is currently working as an Assistant Professor at the Department of Computer Science, Lahore Garrison University, Lahore, Pakistan. Before joining the Lahore Garrison University, he has worked in various academic and industrial roles in Pakistan. He has been teaching graduate and undergraduate students in computer science and engineering for the past 12 years. He is currently guiding four Ph.D. scholars and four M.Phil. scholars. He has published about 150 research articles in international journals as well as reputed international conferences. His research interests include MUD, image processing and medical diagnosis, and channel estimation in multi-carrier communication systems using soft computing with various publications in journals and conferences of international repute. He received the Scholarship Award from the Punjab Information Technology Board, Government of Punjab, Pakistan, for his B.S. and M.Phil. degrees, and the Scholarship Award from the Higher Education Commission, Islamabad, for his Ph.D. degree.

SHAZIA SAQIB (Member, IEEE) received the the master's degree in computer sciences from the Department of Computer Science, Quaid-i-Azam University, Islamabad, Pakistan, and the M.Phil. and Ph.D. degrees from the Department of Computer Science, Government College University, Lahore, Pakistan. She is currently working as the Dean of the Faculty of Computer Science, Lahore Garrison University, Lahore. Her research interests include image processing, deep learning, and machine learning.

TAHIR ALYAS (Member, IEEE) received the master's degree in computer sciences and the Ph.D. degree from the School of Computer Science, NCBA&E, Lahore, Pakistan. He is currently working as an Assistant Professor at the Department of Computer Science, Lahore Garrison University, Lahore. His research interests include cloud computing, the IoT, and intelligent age.

ANEES UR REHMAN received the B.S. degree in software engineering from the University of the Punjab Lahore (PUCIT). He is currently pursuing the M.Phil. degree from the Department of Computer Science, Lahore Garrison University, Lahore, Pakistan. He is working at Systems Limited Pakistan, as an Advisory Software Engineer. He also have development experience in different domains of software development i.e., mobile development (native and cross-platform), web development (angular, react, ASP.net core, and python) cloud, and machine learning. His research interests include big data processing, artificial intelligence, cloud computing, and business intelligence.

YOUSAF SAEED received the M.S. degree in broadband and high-speed communication networks and the Ph.D. degree in cognitive VANETs from the University of Westminster, London, where he achieved distinction in an individual research thesis on IPv6. He is currently working as an Assistant Professor at the University of Haripur, Khyber Pakhtunkhwa, Pakistan. His achievements include the publication of monographs, journal articles, and conference papers. His patent is under review regarding Emergency Vehicles-based Traffic Lights Control System. He acquired four research projects of HEC ICT R&D 2018. He received the International Students Award at the College of North West London.

ASIM ZEB received the B.Sc. and M.Sc. degrees in computer science from the University of Peshawar (UOP), Pakistan, in 2002 and 2005, respectively, and the Ph.D. degree in computer science from University Technology Malaysia, in 2016. He served as a Research Fellow for the Nagoya Institute of Technology, Japan, from 2014 to 2015. He served as an Assistant Professor at the Qurtuba University of Science and Information Technology, from February 2016 to April 2019. He has been serving as an Assistant Professor at the Department of Computer Science, Abbottabad University of Science and Technology, Pakistan, since May 2019. His research interests include self-organized networks, networks architectures and protocols, cognitive radio networks, and supervised machine learning techniques. He has received the MJIIT-Malaysia Scholarship, from 2013 to 2014, and the JASSO-Japan Scholarship, from 2014 to 2015.

MAHDI ZAREEI (Member, IEEE) received the M.Sc. degree in computer network from the University of Science, Malaysia, in 2011, and the Ph.D. degree from the Communication Systems and Networks Research Group, Malaysia-Japan International Institute of Technology, University of Technology, Malaysia, in 2016. In 2017, he joined the School of Engineering and Sciences, Tecnológico de Monterrey, as a Postdoctoral Fellow, where he started working as a Research Professor in 2019. His research interests include wireless sensor and ad hoc networks, energy harvesting sensors, information security, and machine learning. He is a member of the Mexican National Researchers System (level I). He is also serving as an Associate Editor for IEEE ACCESS and *Ad Hoc & Sensor Wireless Networks* journals.

EHAB MAHMOUD MOHAMED (Member, IEEE) received the B.E. and M.E. degrees in electrical engineering from South Valley University, Egypt, in 2001 and 2006, respectively, and the Ph.D. degree in information science and electrical engineering from Kyushu University, Japan, in 2012. From 2013 to 2016, he was a Specially Appointed Researcher at Osaka University, Japan. Since 2017, he has been an Associate Professor with Aswan University, Egypt. He has also been an Associate Professor at Prince Sattam Bin Abdulaziz University, Saudi Arabia, since 2019. His current research interests are 5G, B5G and 6G networks, cognitive radio networks, millimeter wave transmissions, Li-Fi technology, MIMO systems, and underwater communication. He is a technical committee member in many international conferences and a reviewer in many international conferences, journals, and transactions. He is the General Chair of the IEEE ITEMS'16 and the IEEE ISWC' 18.