

Low Level Document

BACK-ORDER PREDICTIONS APPLICATION

LLD History :-

Date	Version	Author
22/08/2023	V1.1	Melbin Biju

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Abstract

Increasing demand of products is a common cause of out of product inventory, and the adoption of backordering to satisfy outstanding customer orders after its occurrence cannot be undermined. However, wrong management of backorders incurs several issues such as delay in product delivery, low customer satisfaction, and many more. Therefore, it is necessary to ascertain products with high tendencies of shortage beforehand in order to undertake proactive measures and potentially mitigate both tangible and intangible costs. Hence, this paper proposes a backorder predictive model using Machine learning techniques on large and imbalanced inventory dataset. The data was pre-processed using Robust Scaler, while data balancing method was applied on the imbalanced data simultaneously and their output were fed into Random Forest Classifier / XgBoost Classifier to predict which item goes on backorder. The evaluation of the result obtained showed had performed better with 0.99 precision, 0.96 recall, and 0.989 F1-Score. The proposed model when compared with other machine learning algorithms shows significant impact on prediction of product backorder.

1. Introduction

1.1. What is Low-Level design document?

The goal of LLD or a low-level design document (LLDD) is to give the internal logical design of the actual program code for Back Order Prediction Model. LLD describes the class diagrams with the methods and relations between classes and program specs. It describes the modules so that the programmer can directly code the program from the document.

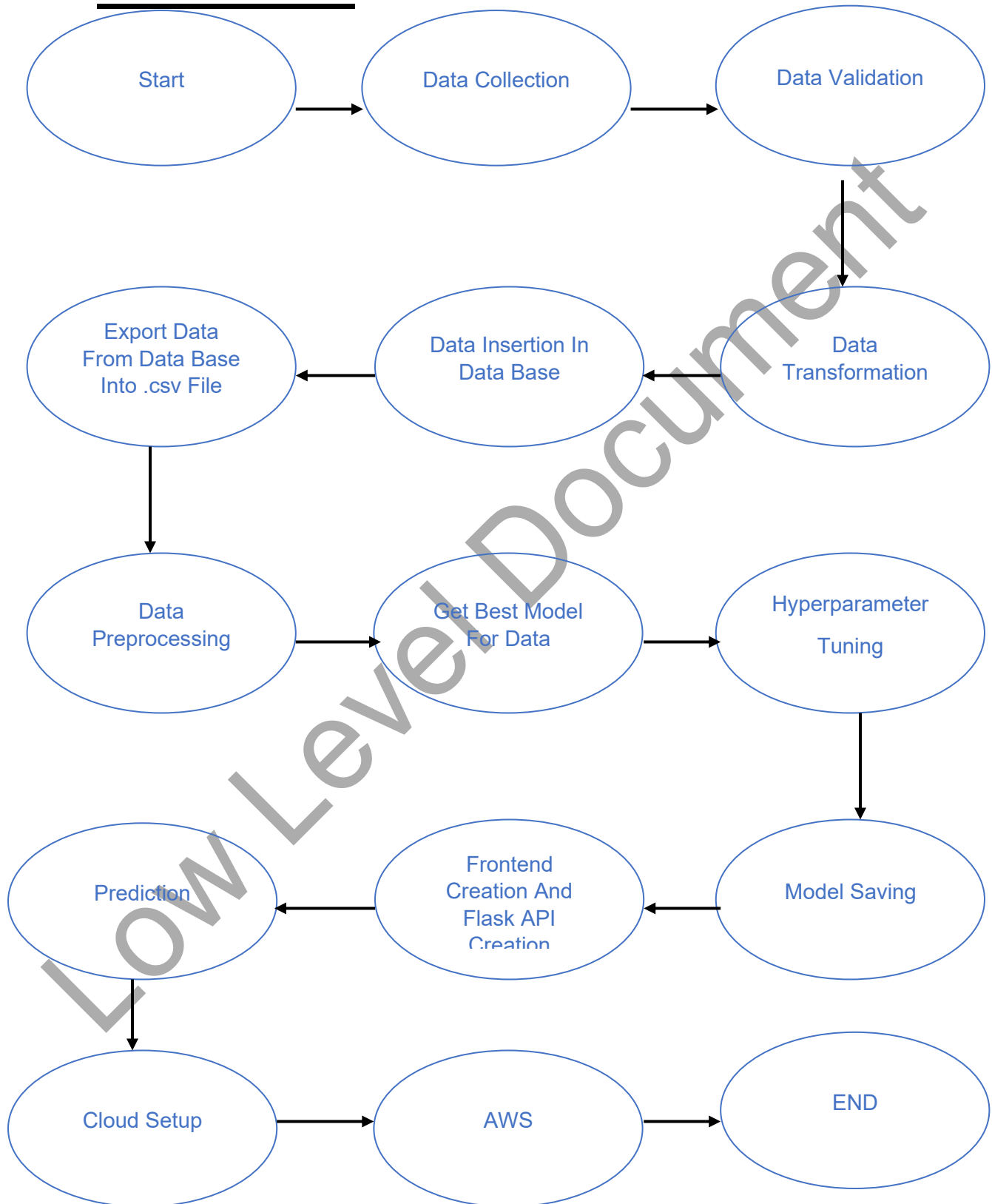
1.2. Scope

Low-level design (LLD) is a component-level design process that follows a step-by step refinement process. This process can be used for designing data structures, required software architecture, source code and ultimately, performance algorithms. Overall, the data organization may be defined during requirement analysis and then refined during data design work.

1.3. Constraints

Internet connection is a constraint for the application. Since the application fetched the data from the database, it is crucial that there is an Internet connection for the application to function. Since the model can make multiple requests at same time, it may be forced to queue incoming requests and therefore increase the time it takes to provide the response.

2.Architecture



3. Architecture Description

3.1. Data Description

We have 2 lakh Dataset row columnar data includes sku , national_inv , lead_time , in_transit_qty , forecast_3_month , forecast_6_month , forecast_9_month , sales_3_month , sales_6_month , sales_9_month , min_bank , potential_issue , pieces_past_due , perf_6_month_avg , perf_12_month_avg , local_bo_qty , deck_risk , oe_constraint , ppap_risk , stop_auto_buy , rev_stop , went_on_backorder. These is given in the comma separated value format (.csv). These data is Given By Company Team which contains both the test data and train data.

3.2. Data Cleaning / Data Transformation

In the Cleaning process, we have cleaned up all the data because data is present in very bad format which was can not recognized by machine .So data Cleaning is done very first by data validation methods. In which we are create a json file in which name of file , numbers of columns etc information present. File name is given in “BackOrder_08012020_120000” Format.

3.3. Exploratory Data Analysis

In EDA we have seen various insights from the data so we have selected which column is most important and dropped some of the columns by observing them spearman rank co-relation and plotting their heatmap from seaborn library also we done null value managed in an efficient manner and also implemented categorical to numerical transfer of column method here.

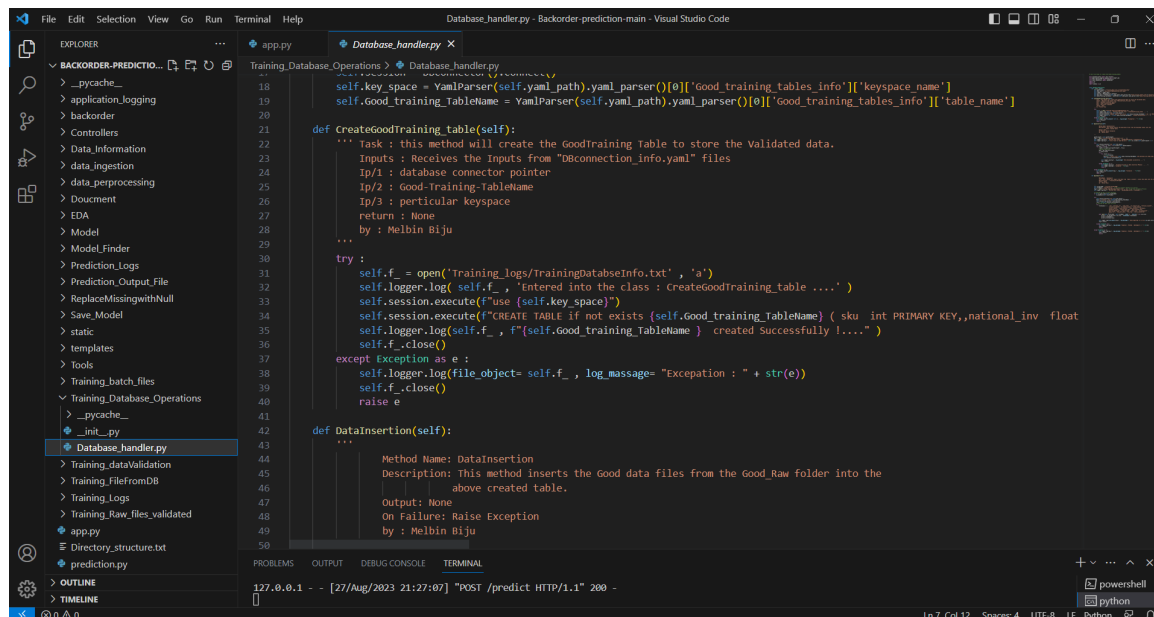
3.4. Event Log

The system should log every event so that the user will know what process is running internally. Logging is implemented using python's standard logging library. Initial step-by-step description:-

- The system should be able to log each and every system flow.
- System must be able to handle logging at greater scale because it helps debugging the issue and hence it is mandatory to do.

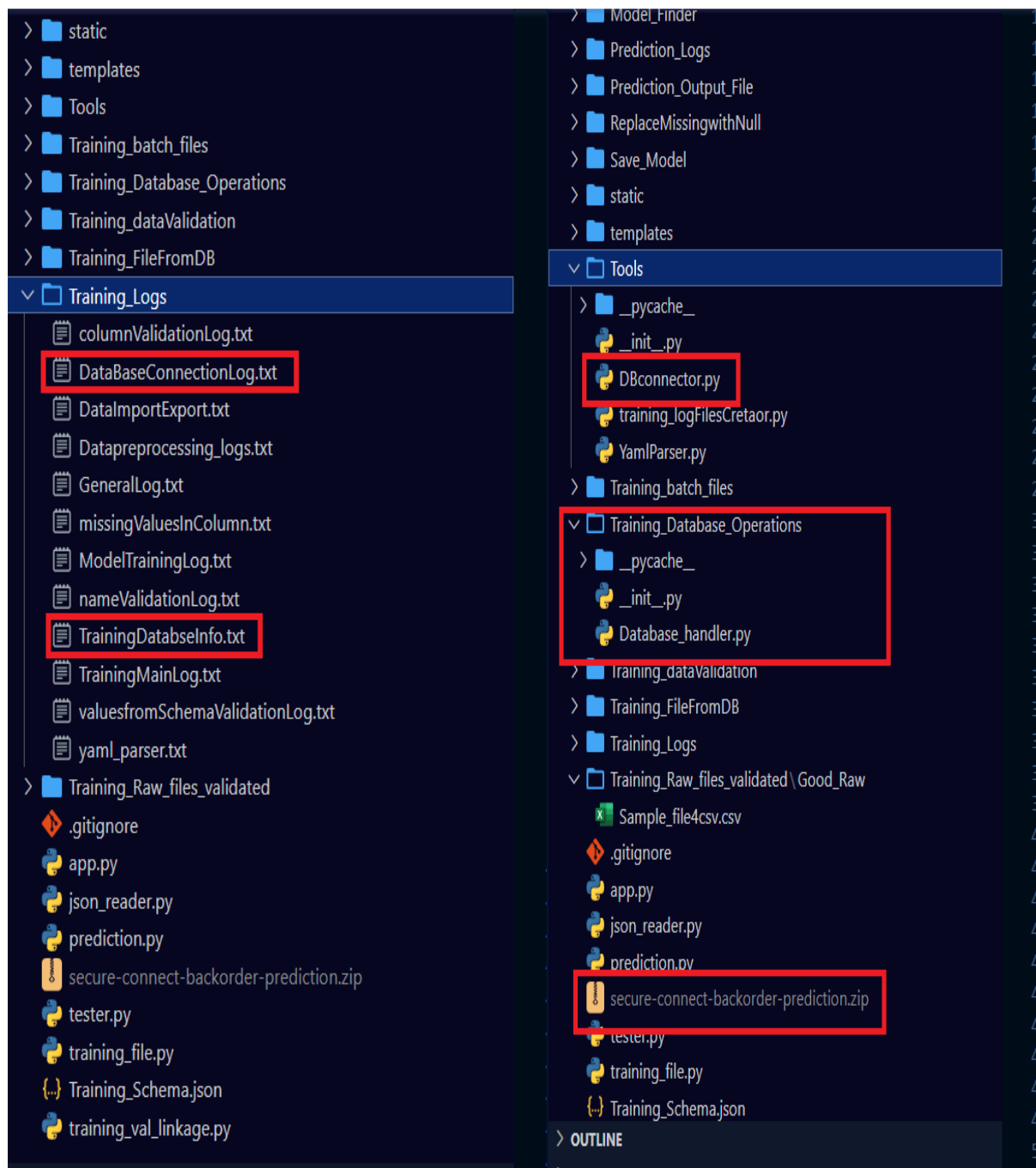
3.4. Data Insertion into Database

- ❖ Database Creation and connection - Create a database with name passed. If the database is already created, open the connection to the database.
- ❖ Table creation in the database.
- ❖ Insertion of files in the table



3.5. Export Data from Database

- ❖ Data Export from Database - The data in a stored database is exported as a CSV file to be used for Data Pre-processing and Model Training.



3.6. Data Pre-processing

Data Pre-processing steps we could use are Null value handling, Categorical to Numerical Transformation of columns , Splitting Data into Dependent and Independent Features , Robust Scaling , Remove those columns which are does not participate in model building Processes , Imbalanced data set handling, Handling columns with standard deviation zero or below a threshold, etc.

3.7. Model Creation / Model Building

After cleaning the data and completing the feature Engineering/ data Per processing. we have done splitted data in the train data and test data using method build in pre-processing file and implemented various Classification Algorithm like RandomForestClassifier and XgBoostClassifier also calculated their accuracies on test data and train data.

	Logistic Regression	XGBoost Classifier	Support Vector Classifier	Random Forest	KNearrest Classifier	Gaussian Naive Bayes	Best Score
Accuracy	0.941960	0.972819	0.945435	0.983600	0.978644	0.935421	Random Forest
Precision	0.989575	0.985004	0.991883	0.994982	0.992221	0.983982	Random Forest
Recall	0.893252	0.960225	0.898160	0.972086	0.964826	0.885174	Random Forest
F1 Score	0.938937	0.972445	0.942686	0.983391	0.978320	0.931943	Random Forest

3.8. Hyperparameter Tuning

In hyperparameter tuning we have implemented randomized search cv or grid search cv and from that we also implemented cross validation techniques for that. From that we have choose best parameters according to hyperparameter tuning and best score from their accuracies so we got 99% accuracy in our random forest classifier after hyper parameter tuning.

3.9. Model Dump

After comparing all accuracies and checked all ROC, AUC curve accuracy we have choose hyper parameterized random forest classifier and xgboost classifiers as our best model by their results so we have dumped this model in a pickle file format with the help of `load_model` and `find_best_model` method build in `save_model.py` python module.

3.10. Data from User

Here we will collect user's requirement to predict whether a product in backorder or not their forecast_3_month, forecast_6_month, forecast_9_month, sales_3_month, sales_6_month, sales_9_month, perf_6_month_avg, perf_12_month_avg .

3.11. Data Validation

Here Data Validation will be done, given by the user.

3.12. Model Call for specific input

Based on the User input will be throwing to the backend in the variable format then it converted into pandas data frame then we are loading our pickle file in the backend and predicting whether product come in backorder or not as an output and sending to our html page.

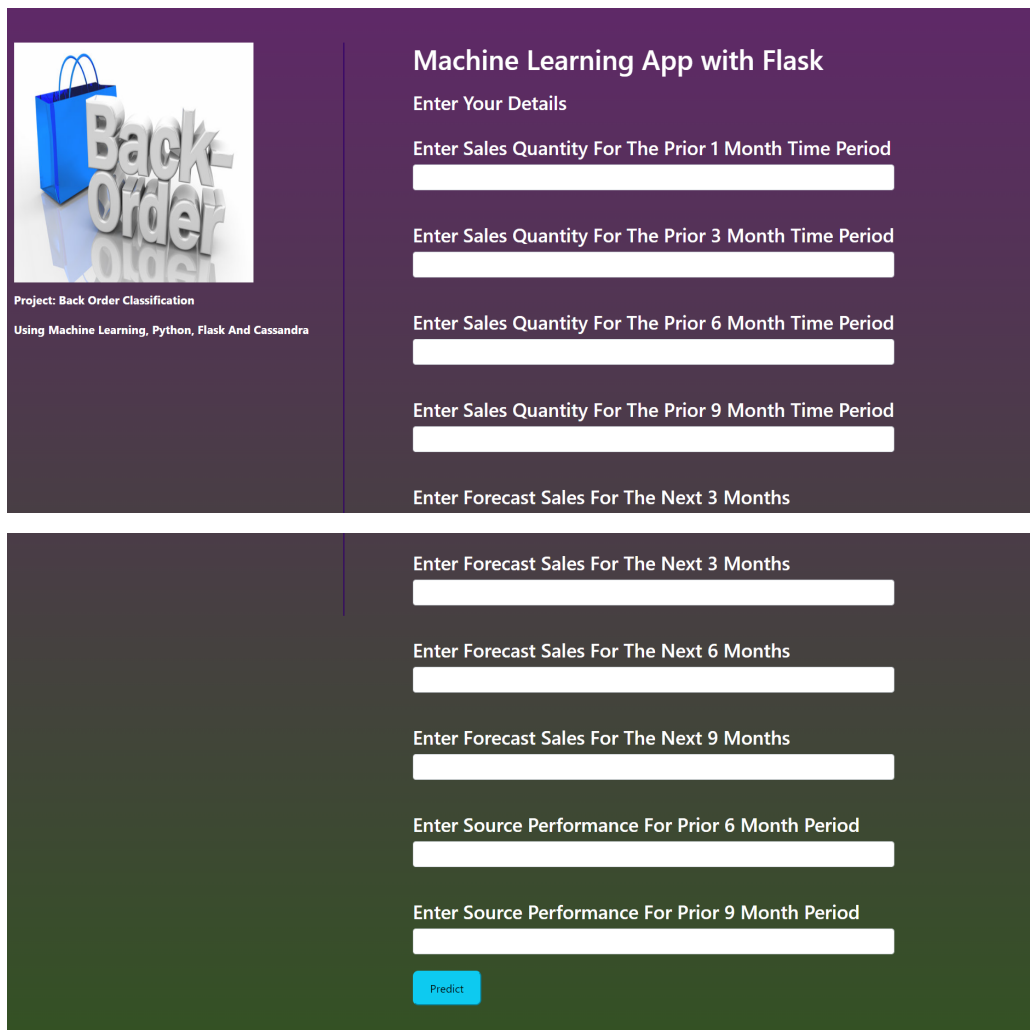
3.13. Saving Output in .csv file

After calling model Recipe/Output will be recommended, this output will be saved in .csv file and it will be used to show the Output.

3.14. User Interface

In Frontend creation we have made a user interactive page where user can enter their input values to our application. In these frontend page we have made a form which has beautiful styling with CSS and bootstrap. These HTML user input data is transferred in variable format to backend. Made these html fully in a decoupled format.

Input page :-



Machine Learning App with Flask
Enter Your Details

Enter Sales Quantity For The Prior 1 Month Time Period

Enter Sales Quantity For The Prior 3 Month Time Period

Enter Sales Quantity For The Prior 6 Month Time Period

Enter Sales Quantity For The Prior 9 Month Time Period

Enter Forecast Sales For The Next 3 Months

Enter Forecast Sales For The Next 3 Months

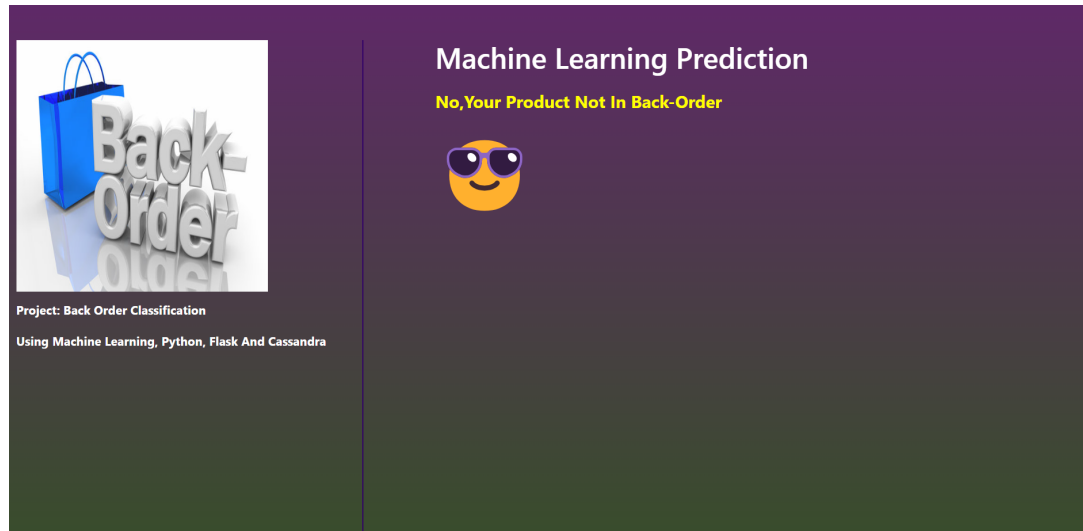
Enter Forecast Sales For The Next 6 Months

Enter Forecast Sales For The Next 9 Months

Enter Source Performance For Prior 6 Month Period

Enter Source Performance For Prior 9 Month Period

Output page :-



3.15. Deployment

We will be deploying the model with the help of AWS cloud platforms.

This is a workflow diagram for the Back-Order Prediction Application



4. Technology Stack

Front End	HTML, CSS, Bootstrap File
Back End	Flask, Pandas, NumPy, scikit-learn etc
Database	Cassandra
Deployment	AWS

5.Directory Tree Structure

```
└── Backorder-Prediction
    ├── application_logging
    │   └── logging.py
    ├── Controllers
    │   └── DBconnection_info.yaml
    ├── Data_Information
    │   └── Null_Values.csv
    ├── data_ingestion
    │   ├── __pycache__
    │   └── data_loader.py
    ├── data_preprocessing
    │   ├── __pycache__
    │   └── preprocessing.py
    ├── EDA
    │   ├── EDA-part1.ipynb
    │   └── EDA-part2.ipynb
    ├── model
    │   └── Random Forest
    │       └── Random Forest.sav
    ├── model_finder
    │   ├── __pycache__
    │   └── Model.py
    ├── Prediction_logs
    │   └── predictionlog.txt
```

- |— Prediction_Output_File
 - | — Predictions.csv
- |— ReplaceMissingwithNull
 - | — __pycache__
 - | — __init__.py
 - | — transformer.py
- |— Save_Models
 - | — __pycache__
 - | — save_methods.py
- |— static
 - | — backorder.jpg
 - | — Style1.css
 - | — Style2.css
- |— Templates
 - | — index.html
 - | — predict.html
- |— Tools
 - | — __pycache__
 - | — __init__.py
 - | — DBconnector.py
 - | — training_logFilescreator.py
 - | — YamlParser.py
- |— Traning_batch_Files
 - | — BackOrder_08012020_120000.csv
- |— Training_Database_operations

- | | — __init__.py
- | | — __pycache__
- | | — Database_handler.py
- | — Traininig_dataValidation
- | | — __pycache__
- | | — RawtrainingValidation.py
- | — Training_FilesfromDB
- | | — InputFile.csv
- | — Training_Logs
- | | — columnValidationLog.txt
- | | — DataBaseConnectionLog.txt
- | | — Datapreprocessing_logs.txt
- | | — GeneralLog.txt
- | | — TmissingValuesInColumn.txt
- | | — ModelTrainingLog.txt
- | | — nameValidationLog.txt
- | | — TrainingDatabseInfo.txt
- | | — TrainingMainLog.txt
- | | — valuesfromSchemaValidationLog.txt
- | | — yaml_parser.txt
- | — Training_Raw_Files_Validated
- | | — BackOrder_08012020_120000.csv
- | — training_val_linkage.py
- | — training_file.py
- | — app.py

- |— prediction.py
- |— requierements.txt
- |— Training_Schema.json
- └— secure-connect-backorder-prediction.zip

Low Level Document

6.Unit Test Case

Test Case Description	Pre – Requisite	Expected Resulted
Verify whether the Application URL is accessible to the user	1. Application URL should be defined	Application URL should be accessible to the user
Verify whether the Application loads completely for the user when the URL is accessed	1. Application URL is accessible 2. Application is deployed	The Application should load completely for the user when the URL is accessed
Verify Response time of URL from backend model.	1. Application is accessible	The latency and accessibility of application is very faster we got in AWS ec2 service.
Verify whether user is giving standard input.	1. Handled test cases at backends.	User should be able to see successfully valid results.
Verify whether user is able to see input fields on logging in	1. Application is accessible 2. User is logged in to the application	User should be able to see input fields on logging in
Verify whether user is able to edit all input fields	1. Application is accessible 2. User is logged in to the application	User should be able to edit all input fields
Verify whether user gets Predict Back-Order button to submit the inputs	1. Application is accessible 2. User is logged in to the application	User should get Submit button to submit the inputs

Verify whether user is presented with recommended results on clicking submit	1. Application is accessible 2. User is logged in to the application	User should be presented with recommended results on clicking submit
Verify whether the recommended results are in accordance to the selections user made	1. Application is accessible 2. User is logged in to the application and database	The recommended results should be in accordance to the selections user made
Verify whether user has options to filter the recommended results as well	1. Application is accessible 3. User is logged in to the application	User should have options to filter the recommended results as well
Verify whether the KPIs indicate details Of the correct inputs	1. Application is accessible 2. User is logged in to the application	The KPIs should indicate details of the suggested inputs to users.