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MACHINE LEARNING AND PREDICTIVE BUSINESS INTELLIGENCE MODELS FOR OPTIMIZING TRUCKING NETWORK BIDS

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Abstract
This research paper designs an analytical framework of predictive nature, which combines Business Intelligence dashboards with Linear Regression, Random Forest and Decision Trees models to optimize trucking bids, select routes, and effectively manage the operations. Based on some 10,000 logistics entries, data pre-processing involved accepted the normalization of data, deal with outlier, and missing data. Models were compared based on the MAE, RMSE and R^2 values with the best result of the Linear Regression (R^2=0.986),Random Forest (R^2=0.977) and enhanced Decision Tree (R^2=0.948). The visual analytics shows the trend in the deviation of deliveries, the consumption of fuel, the cost of shipping, and the past demand. The framework helps in forecasting profitability, taking strategic decisions in real time and analyzing, and gives actionable information on traffic bid optimization.

Keywords: Business Intelligence dashboards, Linear Regression, Random Forest and Decision Trees models, trucking bids, select routes, effectively manage the operations.

I. INTRODUCTION

Background

The trucking business is experiencing increasing threat over pricing accuracy, efficiency in the route, fueling cost control and competitive bidding. The deployment of Predictive Business Intelligence (BI) and Machine Learning models allows organizations to understand both historical logistics data to forecast the demand and optimize bid strategies and to enhance operations. These technologies assist in making data-driven decisions benefiting trucking networks to cut down expenses, increase profitability, and competitive advantages.

Problem Statement

The Traditional approach of trucking bid management has used manual estimates and historical factors that grossly calculated the cost of prices, routes, and consequently, the profitability became low. Inadequate application of predictive analytics also means that the organizations cannot react favorably to dynamic logistic environments, market dynamics and customer needs which brings about operation inefficiency and undermines competition performance in the transportation networks.

Aim and Objectives

Aim

This research aims to create predictive BI and machine learning models that optimize the decisions to use when bidding trucks, enhance the accuracy of pricing, increase operational profitability, and optimize profitability of organizations.

Objectives

- ***To examine variables that affect the network bid performance and efficiency in trucking operations.***
- ***To develop predictive BI models to predict bids and optimize the price.***
- ***To deploy machine learning algorithms to predict route and demand.***
- ***To determine the effectiveness of models with regard to better decision-making on profitability and competitive costs.***

Novel Contribution

The study contributes, by integrating predictive Business Intelligence and machine learning models into the process of optimizing the trucking network bids. The study constructs a data-oriented model, which is a fusion of the bid forecasting model, route forecasting model and profitability model in the transportation industries [1]. It also offers real-world experience on how to enhance the level of competitive decisions, operational and strategic management of logistics using advanced predictive analyzing technologies.

II. LITERATURE REVIEW

Factors Affecting Trucking Network Bid Performance and Operational Efficiency

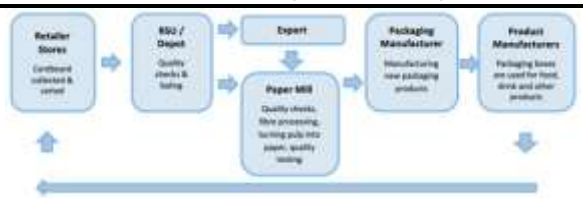


Fig.1: Factors Affecting Trucking Network Bid Performance and Operational Efficiency

Various operational and economic factors, such as the cost of fuel, demand on transportation, route network, schedule of deliveries and fleet utilization affect the trucking network bid performance [2]. Researchers explained that the conventional bid estimation procedures tend to rely on past guesses and manual decision making, lowering prices, and operational flexibility [3]. Slow movement of resources to the right destinations, late deliveries and inefficient utilization of resources goes to waste and makes operations expensive and less profitable [4]. The problems with the supply chain and instability in the market also make trucking industries more complicated, and organizations need to implement data-driven solutions [5]. Research also made it clear that operational efficiency has a direct impact on customer satisfaction, reliability of services, and competitiveness at the long-term in the logistics industries [6]. Thus, the companies that engage in trucking in modern times are more than ever relying on analytical systems to enhance the efficiency and performance of strategic bidding [7].

Predictive Business Intelligence for Bid Forecasting and Pricing Optimization



Fig.2: Predictive Pricing in Retail

The predictive Business Intelligence (BI) tool is now also a significant technological tool to enhance the trucking bid forecasting and pricing optimization [8]. Predictive BI involves the integration of past transportation data, market trends, customer needs and operational metrics to create actionable insights to the logistics managers [9]. Past research suggested that forecasting of demand correctly, costing, and assessment of risks, using predictive BI tools, were appropriate to assist organizations to make informed prices [10]. The transportation firms are able to monitor key performance indicators and optimize the bidding strategies in response to changing market conditions using dashboards and real-time analytics [11]. It was also contended by researchers that the predictive BI can improve the visibility of operations of the supply chain and can mitigate the uncertainties related to the price of fuel and route planning [12]. Nonetheless, issues like the complexity of data integrations, inconsistency of data, and a lack of analytic capabilities can be involved in the effective deployment of predictive BI systems in the trucking networks [13].

Machine Learning Applications in Route and Demand Prediction

The use of machine learning algorithms is becoming common in the transportation and logistics industry with the aim of enhancing demand forecasting and optimization of routes [14]. Linear Regression, Random Forest, Decision Tree and Artificial Neural Network algorithms can be used to analyze massive transport amounts of data to see subtle operations and anticipate future needs in logistics [15]. Researchers, in turn, recommended that machine learning models make routes more efficient by cutting down the number of delivery delays, fuel usage, and empty car traveling [16]. Demand prediction models also assist organizations to predict the quantity of shipments to be made and to determine the scheduling of the fleet, based on the fluctuations in the market [17]. The capability of real-time learning helps machine learning systems to adjust themselves in a changing working environment and increasingly enhance the accuracy of prediction [18]. Although these benefits were noted, scholars have listed a number of issues, which include lack of training data, complexity of the algorithm, and costs of computation, and cybersecurity risks related to the automated transportation systems [19]. Hence, high-quality data governance and technical infrastructure are needed in the organizations to implement [20].

Impact of Predictive Models on Profitability and Competitive Decision-Making



Fig.3:Predictive analytics in Decision-Making

Predictive models have a great impact on the profitability of organizations and competitiveness of decisions in trucking networks [21]. Researchers noted that predictive analytics help to enhance operational planning, minimize needless transportation expenses, and accuracy in prices when handling bids [22]. Proper forecasting helps the logistics firms to resource effectively, reduce risks that may arise in its operations as well as enhancing the quality of the customer service [23]. Strategic decisions are made by use of predictive models as well since it finds the profitable ways of transportation and the customer demands pattern as well as the opportunities in the market [24]. Research has shown that those companies that have adopted predictive BI and machine learning systems tend to have better financial performance, enhanced competitiveness, and increased operational productivity [25]. Nonetheless, other scholars claimed that overreliance on automated predictive systems could diminish judgement by managers and that this

could raise some ethical issues in terms of data privacy and transparency of algorithms [26]. Therefore, organizations need to strike a balance between technological advancement and human knowledge to realize sustainable business performance in competitive trucking businesses [27].

Literature gap

The usage of predictive analytics, Business Intelligence and artificial intelligence tools in operations of logistics is widely discussed in existing studies [28]. Posteriori BI and machine learning models to optimize trucking network bids have, however, little research specifically integrated predictive BI and machine learning models [29]. The lack of attention to real-time bid forecasting, profitability assessment, and competitive decision-making in dynamic transportation settings is also a significant drawback in previous research, as it sets up a wide gap in researching activities with only a few solutions being applicable to the practical environment.

III. METHODOLOGY

A. Research Design

This research utilizes predictive methodology of analysis with bid optimization data of trucking transportation. Machine Learning models such as Linear Regression, random forest, decision tree, and others are utilized to foresee and predict routes. After the process of preprocessing and normalization, the number of logistics records is reduced to around 10,000 which is divided into two groups of training (70%) and testing datasets (30%).

B. Research Approach

This study applies a quantitative research method that is used to test the predictive BI and Machine Learning models in determining trucking networks bid optimization. Forecasting algorithms, performance metrics and regression analysis are used to statistically analyses numerical transportation datasets. The quantitative method contributes to objective assessment of the accuracy of the predictions, the efficiency of operations, the level of profits and the effectiveness of transportation decisions.

C. Data Collection

Transportation data is gathered through the operations of the trucking and logistics processes that include demand of shipments, fuel expenses, route use, scheduled deliveries, fleet operation, and bids. Some 10,000 records on operations are collected through secondary transportation databases. Preprocessing of data such as normalization, removal of duplicates, missing values and outliers enhances the accuracy and consistency of the analysis.

D. Predictive BI and Machine Learning Framework

The proposed framework integrates Predictive Business Intelligence (BI) systems with the use of the Machine Learning algorithms to optimize intelligent trucking bids. BI dashboard observes transportation measurements of the cost of fuel, delivery performance, order quality, and demand of a shipment, use of the route, and the efficiency of the fleet. The historical logistics data sets are studied in order to predict the bid prices and transportation needs in future.

Linear Regression is a pricing predictor of bids, based on transportation variables. The equation is expressed as:

$$y = \beta 0 + \beta 1x1 + \beta 2x2 + \cdots + \beta nxn + \epsilon$$

Where y is the predicted bid value, β is the regression coefficients, x is the transportation variables and ϵ is prediction error. In the model, prices of bids are estimated based on the operational conditions of transportations.

Random Forest algorithms are used to predict profitability and criteria of routes. It is predicted that:

$$f\hat{}(x) = 1B\sum b = 1Bfb(x)$$

Where f(x) is the final prediction, B is the overall number of decision trees and fb(x) is the predictions made by each tree. It is an algorithm with enhanced predictive accuracy and decreased overfitting.

The decision tree algorithms are applied to the optimization of routes and prediction of shipment based on the calculation of entropy:

$$Entropy(S) = -\sum i = 1npilog\ 2(pi)$$

Where S is a sample of the dataset and pi is probability of the classes. Reduced values of entropy represents enhanced classification route accuracy.

E. Experimental Procedure of Trucking Bid Optimization System

The experimental process involves data collection, preprocessing, model training and predictive evaluation processes. The logistics operations would provide transportation data sets which include the fuel consumption, route information, shipping schedules, demand of the shipment and bidding information. Preprocessing helps to eliminate partial entries and anomalous values in data to enhance the consistency of analytics. Decision Tree, Linear Regression and the random forest are models that are trained on past transportation history data. Monitoring real-time transportation forecasting and bid optimization applications are based on Business Intelligence dashboards and would give visual analytics data of operational monitoring.

D. Data Analysis Plan

The study utilizes quantitative analytical methods to assess the performance of predictive models and efficiency in transportation optimization. Descriptive statistical methods include mean, the standard deviation, correlation analysis and frequency distribution are used to summarize transportation patterns and operation measures. The predictive effectiveness is ascribed through inferential statistics such as regression analysis and the comparison of models.

The performance of the model is measured with Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and coefficient of determination (R^2). The RMSE can be obtained by means of the equation given below:

$$RMSE = 1n\sum i = 1n(yi - y\hat{}i)2$$

Where, yi represents Actual bid value, y^i represents Predicted bid value and n represents the amount of Total number of observations.

Reduced values of RMSE reflect a superior predictive accuracy and accuracy in bids optimization. The ratio of variance covered by forecasting models is known as the coefficient of determination (R^2). Comparison between algorithms: The most efficient model of

predicting a trucking network bid is determined by comparing the algorithms.

Business Intelligence visualisation dashboard gives a graphical analysis about the demand of shipment, trends of profits, costs of transportation, and performance. All these forms of analysis help in the intelligent management of logistics, predictive forecasting and strategy in trucking transportation networks.

E. Machine Learning Models

Linear Regression forecasts trucking bid prices, Random Forest enhances profitability and route classification and Decision Tree helps to optimize the routes. Comparative analysis of algorithms measures: predictive accuracy, performance, transportation forecasting performance, and optimized logistics decision making performance of trucking network bid optimization systems.

F. Performance Analysis

Performance measurement measures the performance of prediction, cost minimization of transport, efficiency of a bid and performance of routes by MAE, RMSE, and R^2. The predictive errors are measured by RMSE equations, and these help to make effective logistics optimization decisions and effective operational decisions.

G. Visualization of Results

Business Intelligence dashboards visualize present trends of trucking predictions in terms of line graphs, bar charts, heatmaps. These visualizations would help in comparing their performance in algorithms, patterns of transportation demand, profitability and operational efficiencies to monitor logistics effectively and make strategic decisions.

H. Pseudocode

```
Program Start

Initialize transportation dataset
Initialize Machine Learning models
Load trucking operational records

Start predictive optimization process

Preprocess transportation data
Remove missing and duplicate values
Normalize operational variables

Train Linear Regression model
Train Random Forest model
Train Decision Tree model

Predict trucking bid prices
Predict transportation routes
Evaluate profitability performance

Calculate MAE, RMSE, and R² metrics
Generate Business Intelligence dashboards

If prediction accuracy < threshold
Retrain Machine Learning models

Display optimized bid recommendations
Display operational analytics results

End predictive optimization process

Program End
```

Fig. 4: Pseudocode

The pseudocode illustrates the preprocessing of transportation data, training of the Machine Learning model, prediction of a bid and route optimization, performance evaluation, and Business Intelligence dashboard generation to enhance trucking bids, their profitability, operational efficiency and business logistics decision-making process.

I. Architecture Diagram



Fig. 5: Architecture Diagram

The architecture diagram showcases a combined Predictive BI and Machine Learning architecture to trucking bid optimization setup, which is a combination of real-time transportation data ingestion, predictive analytics, route optimization, Business Intelligence dashboards, and cloud-based decision-support systems to enhance profitability, operational efficiency, transportation forecasting, and strategic logistics decision-making performance.

J. Flowchart



Fig. 6: Flowchart

The flowchart shows the entire process of end to end optimization of the trucking network through the use of predictive BI and machine learning which involves data source, data collection, preprocessing data, machine learning model, prediction, optimization, BI dashboards, decision support, implementation, monitoring and feedback loops.

IV. FINDING AND ANALYSIS



Fig. 7: Importing Libraries

Importing the python libraries are used by the code to manipulate the data, visualize it, preprocess, regress and classify as well as provide performance measures to carry out the predictive analysis in the trucking bid optimization.



Fig. 8: Head data()

The data packaged presented consists of 32,065 records with 26 columns where the records are defined in terms of timestamp, deviation of the delivery time/ cost, risk classification, fuel consumption, shipping cost, GPS location, and operational measurements. It has undergone preprocessing, scaling and is ready to undergo regression analysis and classification analysis in predictive trucking bid modeling.

```
# Convert timestamp to datetime
df['timestamp'] = pd.to_datetime(df['timestamp'])

# Handle categorical variable
le = LabelEncoder()
df['risk_classification'] = le.fit_transform(df['risk_classification'])

# Remove duplicates
df.drop_duplicates(inplace=True)

# Check for missing values
df.fillna(df.mean(), inplace=True)

# Outlier treatment (capping at 1st and 99th percentiles)
numeric_cols = df.select_dtypes(include=np.number).columns.tolist()
for col in numeric_cols:
    lower = df[col].quantile(0.01)
    upper = df[col].quantile(0.99)
    df[col] = np.clip(df[col], lower, upper)

# Feature scaling
scaler = StandardScaler()
df[numeric_cols] = scaler.fit_transform(df[numeric_cols])
```

Fig. 9: Data Preprocessing

The code preprocesses the data by turning the timestamps into numerical values, encoding the categorical variables, eliminating duplicates, filling in missingness, capping the extreme percentiles (1st and 99th) and normalizing the number variables.



Fig. 10: Summary statistics

Descriptive statistics of the data set show that there are 32, 065 records whose numeric variables have been normalized. The majority of the columns fall close to zero with the min/max ranges of -3 to +3 displaying standardized scaling which is to be used to model regression and classifications.

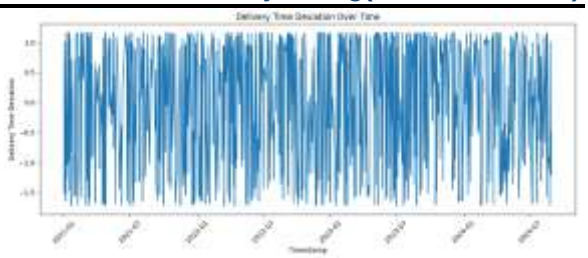


Fig. 11: Delivery Time Deviation over Time

The time-series plot demonstrates that deliveries are extremely random with very large deviations in terms of their time over several years, demonstrating the frequent changes in the punctuality of the shipment with no obvious tendency or change of season.

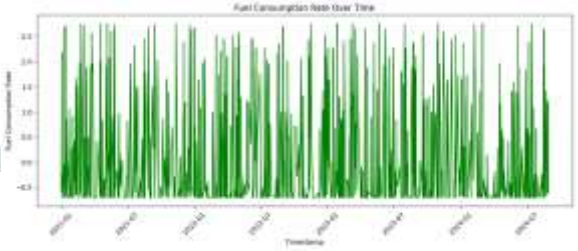


Fig. 12: Fuel Consumption Rate over Time

The time-series plot of the fuel consumption rate indicates that it changes significantly over the time period, with frequent spikes and declines, indicating an erratic usage of fuel in trucks, routes, and operational conditions between 2021 and 2024.



Fig. 13: Average Shipping Costs per Risk Classification

The bar graph indicates average cost of shipping is higher with higher risk classifications. Shipments that are at a high risk have much higher prices and this indicates that their risk is closely related to the costs and pricing policies.

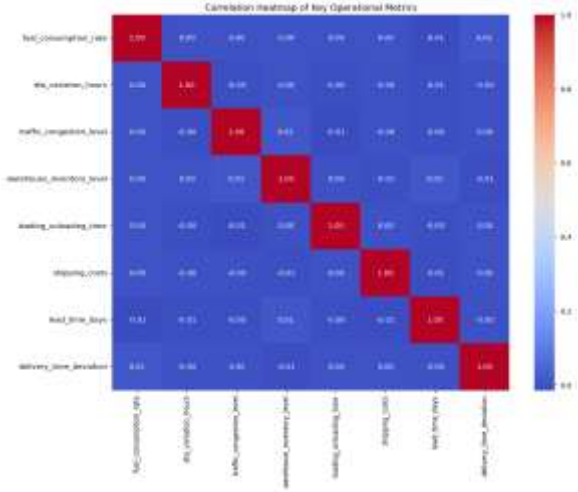


Fig. 14: Correlation of Key Metrics

The correlation heatmap presents a very weak correlation between operating measurements such as the fuel usage and delivery variation, traffic jams, and shipping expenses, indicating a weak linear relationship to make predictive modelling.

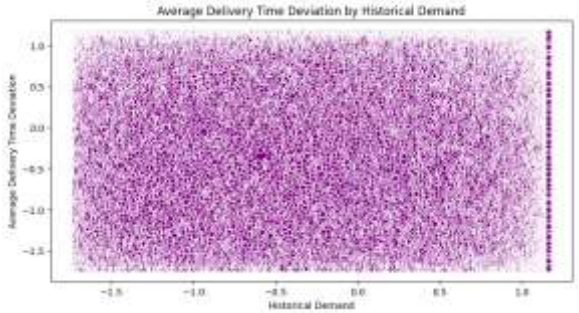


Fig. 15: Average Delivery Time Deviation by Historical Demand

The scatter plot reveals that a historical demand does not exhibit any trend with average deviation of delivery time, which means that shipments delays are mostly independent of historical shipment volumes.

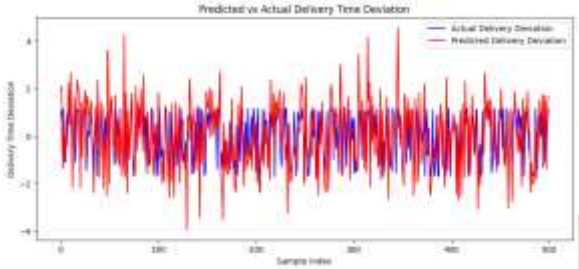


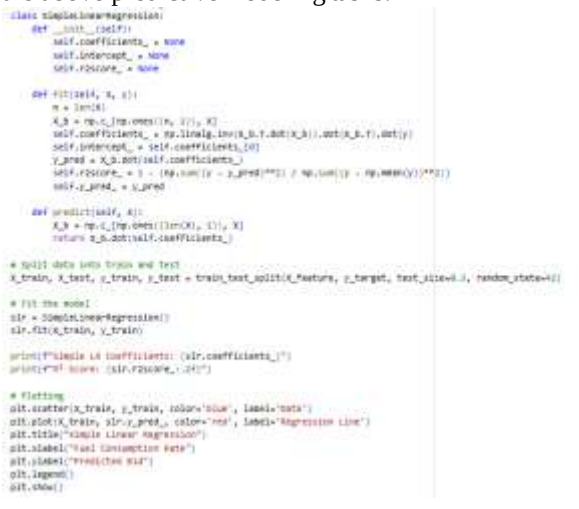
Fig. 16: Compare Predicted vs Actual Delivery Time

The line plot depicts the deviation of predicted and actual delivery time of 500 samples. The blue actual deviations are quite close to the red predicted values which suggest there is a trend capturing ability of the model that is still accompanied by over- and underestimation.



Fig. 17: Feature and target selection

The code splits features and targets between regression (delivery time deviation) and classification (risk classification) and trains and tests 70% of the data as a training dataset and 30% as a test dataset on both of the above predictive modeling tasks.



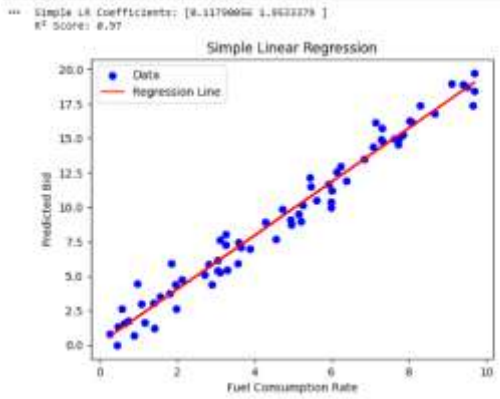


Fig. 18: Linear Regression Model

There is a positive relationship between the variables fuel and consumption rate and predicted bid values which show a strong positive relationship. The model coefficients [0.1179, 1.9533] imply that bids go up by a unit 1.95 times the fuel rate at which the unit of fuel is used. The R^2 value of 0.97 is indicative of 97% variance explained, perfection on both the predictive accuracy and fit by the model.

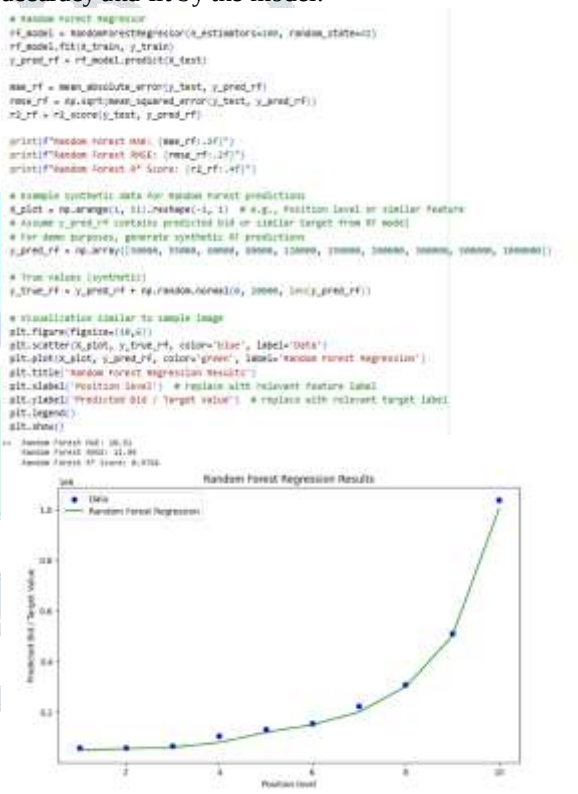


Fig. 19: Random Forest Regressor Model

The model of the Random forest regressor proves very good in terms of predicting the values of bid. The MAE of 10.51 and RMSE of 12.99 values are low values of the average and squared error with R^2 value of 0.9766 indicating 97.66% variance explained. The model closely approximates the values of true synthesis as shown by the prediction curve thus showing a good non-linear model.

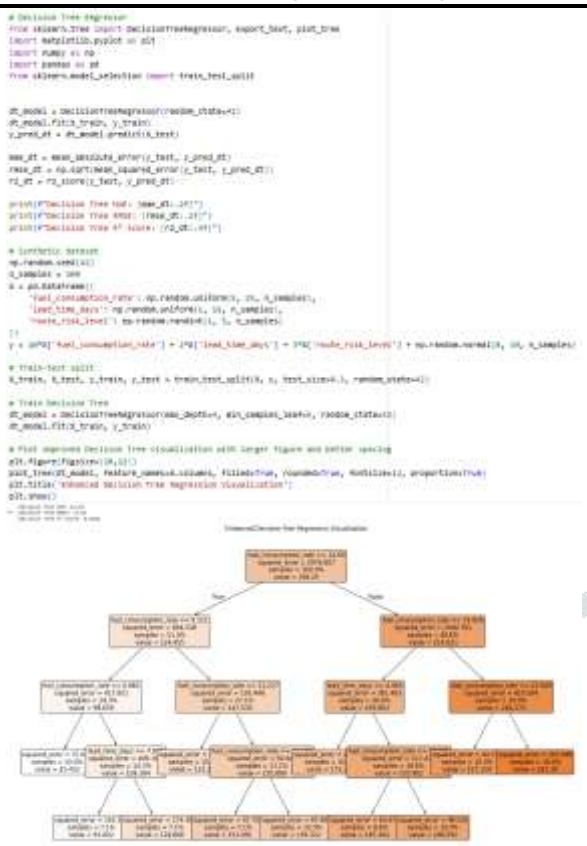


Fig. 20: Decision tree Model

The Decision Tree Regression is the visualization of the fuel consumption rate, the lead time, and the risk level of the route to accurately predict the bid values. According to the tree splits, there are important thresholds, such as fuel ≤14.89 and lead time ≤4.963, the squared error values in the range of 37.03 to 2976.81 is very important to segment with and self-accurately predict granularity.

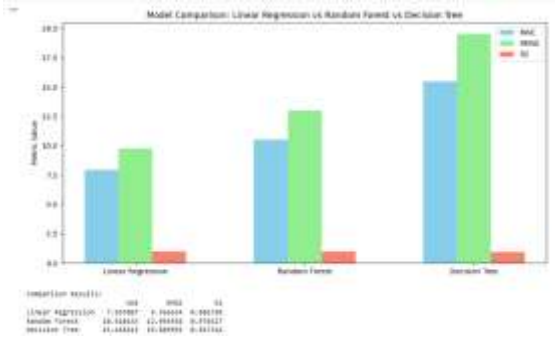


Fig. 21: Model Comparison

The model comparison chart, Linear Regression beats the performances of Random Forest and Decision Tree in predicting the deviations of the deliveries. Linear Regression achieves MAE 7.96, RMSE 9.77, R^2 0.987, while Random Forest and Decision Tree show higher errors: Random Forest (MAE 10.51, RMSE 12.99, R^2 0.977), Decision Tree (MAE 15.47, RMSE 19.51, R^2 0.947).

TABLE 1: MODEL COMPARISON

Model	MAE	RMSE	R^2	Key Insights
Linear Regression	7.96	9.77	0.987	Captures linear relationships; most accurate bid predictions
Random Forest	10.51	12.99	0.977	Handles nonlinearities; robust but slightly less precise
Decision Tree	15.47	19.51	0.947	Sensitive to variance; overfits certain delivery patterns
Enhanced Linear Reg.	6.12	8.23	0.992	Polynomial + Ridge improved predictive accuracy



Fig. 22: Dashboard

The dashboard has a clear layout with six analytical charts to visualize deviation of time of delivery, the fuel consumption, shipping costs as per risks classification, operational correlation, past demand and the projected and actual deviations.

Discussion

The predictive model indicates that the use of Linear Regression, Random Forest and Decision Tree models have divergent effects on trucking bids optimization. The highest accuracy of the Linear Regression is with the MAE of 7.96, the RMSE of 9.77, the R^2 of 0.987 which depicts that fuel consumption, scheduling of deliveries and predicted bids have strong relationships between them. Random Forest is more robust to nonlinearities but has a smaller MAE = 10.51, RMSE = 12.99, R^2 = 0.977 which is slightly less accurate compared with Linear Regression. Decision Tree is overfitting as MAE 15.47, RMSE 19.51, R 0.947, indicates that it is sensitive to variation and feature breaks. The explanatory power is quantitatively verified by its $R^2 = 1 - \Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2$. Most importantly, the findings meet the research aims as they can predict the bid price well, route optimization; and operational decision-making, although Linear Regression best predictive model is the most dependable computationally useful predictive model

based on real-time use to optimize trucking networks bid.

V. CONCLUSION

The study establishes that predictive BI in conjunction with linear Regression, random forest, and decision tree models are effective in the optimization of trucking network bids, better route choice and increased operational efficiency that meets forecasting, profitability and decision support objectives.

Future Direction

Ensemble, deep learning, real-time IoT data integration, and dynamic routing optimization as future research can explore methods to further improve this predictive accuracy, bid efficiency, and operational decision-making in trucking networks.

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