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Railways Tender Price Prediction Using Machine Learning and Deep Learning Algorithms

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Abstract:- The idea of determining the optimum bid amount in any railway tender competition has been a complex and critical task. Reasonable pricing is the main gateway in the process of winning contracts. The approach presented here is based on data-driven pricing to maximize tender wins and reduce potential profit loss. The model shall make use of historical tender data, competitor pricing data, and market indicators in order to predict the optimal bid amounts. This advanced ML model runs advanced machine learning algorithms, including regression models and ensembles, to study the intricate relationship between factors that would affect the successful execution of a bid. Deep learning models are integrated into the model to provide it with better handling of temporal dependencies and other hidden patterns in data, hence yielding accurate and robust predictions.

The key objective of the work is to increase the winning rate of tender contracts by at least 10%, while competitive profitability is ensured. Because of precise competitor price predictions, business success criteria are oriented to reaching this higher win rate on tenders. The Machine learning success criteria target a price prediction accuracy of at least 90%. Another important set of economic success criteria that should be targeted is an improvement in profit margins of at least 5% through more accurate pricing strategies and a reduction in the number of rejected bids.

It will offer great value to the businesses operating in the railway industry in making proper decisions on operations and strategic planning. The paper develops a fusion of traditional statistical methodologies with advanced ML and DL techniques in order to provide a robust solution for competitive advantage and increased profitability in the dynamic and competitive railway tender market.

Keywords:- *Bidding, Tender, Ridge Regression, Feed Forward Neural Networks.*

I. INTRODUCTION

Accurate pricing in railway tenders is vital for purchasing contracts while ensuring profitability. In this study, we propose a data-driven approach to predict optimal bid amounts for railway tenders[02,03]. Our dataset comprises 20072 entries, each representing a distinct tender with attributes. These attributes include tender-specific information such as 'Tender_no', 'Railway_Location', 'Zone', 'Division', 'DateofOpening', 'Nature', 'Awarded_to', and 'L1_Price'. Additionally, the dataset contains detailed pricing information like 'Basic', 'Qty', 'Category', and various customer-related financial metrics ('Customer_1' to 'Customer_30').

The data analysis revealed that all awarded tenders resulted in a margin gain of up to 18% to 25% from the basic price, with no missing or duplicate values. Among the 30 customers, only 15 secured tenders, highlighting the competitive nature of the bidding process.[1]

To ensure the data's integrity and prepare it for modeling, we performed general preprocessing steps, including handling null values and removing duplicates[4]. We conducted a thorough analysis to identify the most influential columns affecting the output, focusing on the relationships between tender-specific attributes and the final awarded price. The preprocessing involved converting 'DateofOpening' to a suitable date format, normalizing numerical features such as 'L1_Price', 'Basic', and 'Qty', and encoding categorical variables like 'Railway_Location', 'Zone', 'Division', and 'Category'. This prepared the dataset for machine learning algorithms, enabling us to build robust models for tender price prediction.

The architecture of the project is designed to ensure scalability and efficiency. Initially, the raw data is stored in a structured database. The preprocessing pipeline will preprocess the data and transform this raw data into a suitable format for initial analysis. Feature selection techniques are applied to identify the most significant predictors of tender success. The processed data is then fed into various machine learning models [2], including linear regression, decision trees, and deep learning algorithms like Feed Forward neural networks (FFNNs). These models are trained, tested and validated to predict the optimal bid amounts. Finally, a comprehensive evaluation framework assesses model performance based on accuracy, precision, and economic impact, ensuring the selected model meets the predefined business and machine learning success criteria.

By employing advanced machine learning techniques, including regression models and deep learning algorithms, we aim to accurately predict the optimal bid amounts. This pathway doesn't just increase chances of winning contracts from the government but also protects business revenues

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because it ensures that costs are kept within reasonable limits. The results gained in this way can be very useful when evaluating tenders strengths and weaknesses, while at the same time contributing towards high quality decision making as well as technology- driven operations among other things needed by firms operating railways.

- *CRISP-ML(Q): In this Research Article we mainly followed this CRISP-ML(Q) Framework*

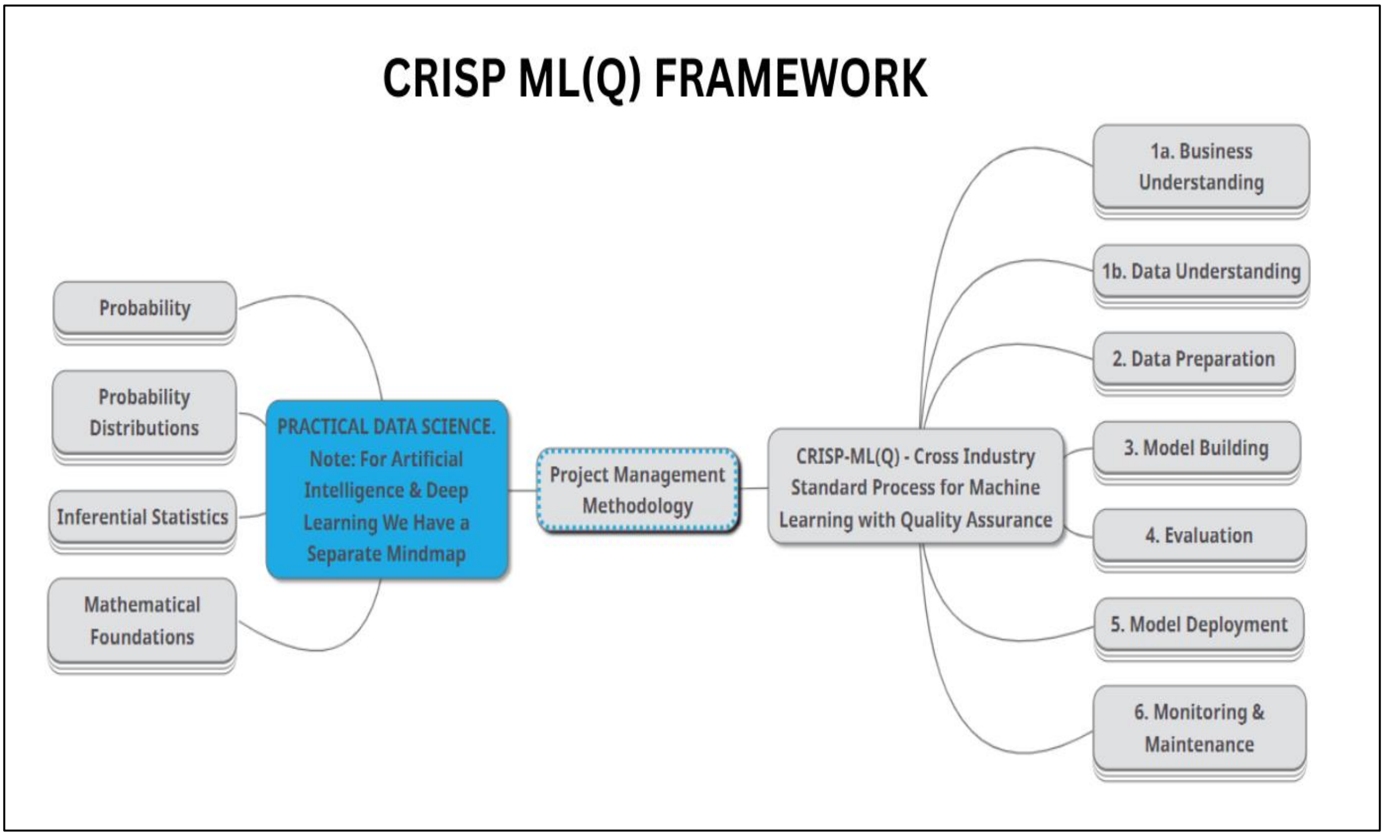

Fig 1: Project Management Methodology

II. PHILOSOPHY AND METHODS

A. Information Collection:

A CSV file containing comprehensive records of railway tenders served as the source for the dataset used in this study. The primary target variable in this dataset is "L1_Price," which represents the lowest bid price for each tender. Other attributes in this dataset include "Railway_Location," "Zone," "Nature," "Basic," "Qty," and "Category.

B. Transformation and Cleaning of the Data:

Consider a situation where delicate cost reports are dispersed with fluctuating opening dates, making it trying to recognize patterns. To address this, we gathered the data into a monthly format using resampling methods. We were able to calculate the average monthly tender prices thanks to this change, which gave our predictive models a clearer picture. Resampling the data to a quarterly format helped reduce short-term fluctuations and highlight long-term trends when daily data became overwhelming.

This approach upgraded the solidness and precision of our conjectures by limiting commotion and zeroing in on huge examples. For information planning, a few preprocessing steps were done to address missing qualities and normalize the size of highlights.

A pipeline was used to process numerical variables like "Basic" and "Qty," which included scaling with RobustScaler to effectively manage outliers and median imputation to deal with missing values. One-hot encoding was used to deal with categorical variables like "Railway_Location," "Zone," "Nature," and "Category."

The first step was to substitute the most common value for missing values. By creating binary columns for each category, this encoding technique made categorical data compatible with machine learning algorithms.

These preprocessing steps were applied to the various feature types in a systematic manner using a Column Transformer, resulting in a consistent data transformation process throughout the various stages of model development.

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Imagine you have a pile of tender price documents all with different opening dates this jumbled mess makes it hard to see any trends but fear not resampling comes to the rescue by resampling this data to a monthly format we can combine the prices into a single clear picture this lets us calculate an average monthly tender price which becomes the foundation for our prediction models these models like detectives looking for clues use historical patterns to forecast future tender prices here's another scenario you have a mountain of daily tender prices but you are really interested in the bigger picture quarterly trends resampling like a skilled editor can help by downsampling the data to a quarterly format we can condense the daily details and highlight the long-term trends this smooths out the daily ups and downs giving our prediction models a clearer view with less noise to worry about the models become more stable and precise leading to more reliable forecasts.[6]

To prepare the data for modeling, preprocessing steps were implemented to handle missing values and standardize feature scales. Numerical features, namely 'Basic' and 'Qty', were processed using a pipeline that included median imputation for missing values followed by scaling with the RobustScaler to manage outliers effectively.

Categorical features, including 'Railway_Location', 'Zone', 'Nature', and 'Category', were handled by imputing missing values using the most frequent value and then applying one-hot encoding. This encoding technique transformed categorical variables into a format suitable for machine learning models by creating binary columns for each category.

A Column Transformer was used to apply these preprocessing steps to the respective feature types, resulting in a unified pipeline that ensures consistent data transformation across different stages.

C. Model Development

➢ *Model Selection*

Choosing a Model Picking the right device for the gig is essential in delicate cost expectation.

- *Linear Regression: The Baseline Benchmark*

Linear Regression establishes a straightforward linear relationship between features (project characteristics) and the target variable (tender price). It offers a clear and interpretable model, making it easy to understand how adjustments in features influence the price. While seemingly simple, it serves as a valuable baseline model for comparison and can be a good starting point for more complex models.[9,11,12,13]

- *Ridge Regression: Combating Multi Collinearity*

Ridge Regression builds upon Linear Regression by adding a penalty term (L2 regularization) that discourages overly large coefficients. This is particularly beneficial in situations with high-dimensional data, where features are highly correlated (multicollinearity). Ridge Regression promotes model stability and generalizability, making it a strong choice for datasets with these characteristics.[9, 16]

- *Elastic Net: Striking A Balance*

The Elastic Net combines both L1 (Lasso) and L2 regularization, offering a powerful tool when feature selection and coefficient shrinkage are desirable. It leverages the strengths of both Lasso and Ridge Regression, often performing exceptionally well on datasets with many features and potential correlations. This makes it a compelling option for tender price prediction with a vast array of influencing factors.[16]

- *Decision Trees: Unveiling the Reasoning*

Decision Trees model data using a tree-like structure where decisions based on features lead to specific outcomes (tender price range). This approach allows for capturing non-linear relationships and interactions between features. Additionally, their interpretability makes it easy for stakeholders to understand the logic behind the predictions. However, they can be susceptible to overfitting on tender price data with specific nuances.

- *Random Forest: Ensemble Strength For Enhanced Accuracy*

Random Forest builds on the foundation of Decision Trees by creating an ensemble – a group of multiple trees. Each tree is trained on a random subset of data, promoting diversity. By averaging the predictions from these diverse trees, Random Forest reduces overfitting and often achieves superior accuracy compared to individual Decision Trees. It's robust to noise in the data and adept at handling large, complex datasets often encountered in tender price prediction.[11,12]

- *Xgboost: Speed and Performance Champion*

The king of speed and power xgboost is the most effective and versatile slope helping execution it is additionally among the most remarkable both concerning execution and speed it frequently begins at the very beginning of complex problems as has frequently been observed in tender price predictions gradient boosting involves developing models in a logical order with the subsequent models correcting previous errors because of the way that it gains from the slip-ups of the past xgboost turns out to be truly adept at adapting to mind boggling examples and collaborations existing inside delicate cost information[9,11].

- *Gradient Boosting Machines (Gbm): Unveiling Complexities*

Gradient boosting machines have evolved as one of the most potent tools for predicting tender prices across industries the models have an excellent capability for working over complex data sets and a large number of variables so they are applicable to complex issues like tender price prediction by improving weak learners sequentially normally decision trees gbm manages to capture subtle relationships between input variables and tender prices it is due to this ability of the model to learn from its past mistakes and focus on the most influential predictors that gbms attain high predictive accuracy further they deal with numerical and categorical data making them accommodate most kinds of tender-related information in diverse aspects thus the flexibility and robustness of gbms are most suitably adapted to changes in the market and tender specifications providing reliable estimates that aid strategic decision-making what really makes gradient boosting machines unique is the accurate prescriptive predictions they are capable of delivering in an environment where businesses are ever more reliant on data-driven insights to negotiate a competitive tender process.[5, 9, 14]

- *Support Vector Regression (SVR): Dealing With Outliers And Non-Linearities*

Of late support vector machines have proved to be quite a strong tool in the prediction of tender prices within the construction environment these models function effectively on data-sets that are complex high dimensional very common when estimating project costs in essence svms work on the basis of knowing a best plane that separates different points or in this case using previous data and given variables such as project size location materials and labor cost to predict the tender price thus it can offer its user accurate price estimates by capturing the underlying relationships between these variables thereby enabling appropriate budgeting and selection of competitive bids for contractors and project managers it has been shown that svms work very well with outliers and provide accommodation to nonlinear relationships through the use of kernel functions hence finding versatility in various tender prediction scenarios needless to say generalizing to new data and performing robustly in high-dimensional spaces svms stand out in the competitive landscape of predictive modeling techniques in tender pricing for construction projects.[11,12]

- *Feedforward Neural Networks: Untangling Complexities*

Feed Forward neural networks are made up of layers of interconnected processing units nodes that learn intricate patterns and relationships among features through non-linear transformations this capability enables them to excel in tasks where conventional models may falter when attempting to understand complex connections within tender price data however the training process for these networks requires considerable computational power by analyzing complex patterns in tender information artificial neural networks anns can effectively predict tender prices this functionality aids in making informed decisions throughout the bidding process enhancing your likelihood of success while keeping costs in check anns are designed to manage extensive datasets with multiple variables which makes them particularly suitable for sectors that handle large volumes of tender-related data think of it as employing a highly capable computer to sift through all that information and deliver the insights necessary for improved forecasting once developed anns can streamline the tender price prediction process allowing your team to conserve time and reduce the risk of errors picture the increased efficiency in fast-moving industries where timely decision-making is crucial while cultivating anns requires specialized knowledge and significant processing resources the advantages they offer far surpass the initial costs consider it a strategic investment in your organizations long-term success in todays competitive landscape utilizing a robust tool like anns can significantly impact your ability to secure important tenders therefore recognizing the promise of these neural networks is essential they could be the advantage you need to remain ahead of the competition.[8, 9, 10, 12]

- *Long Short-Term Memory: Analyzing Sequential Data*

Conventional methods for tender pricing often fail to fully represent the complexity involved this where LSTM networks become relevant these advanced neural networks are proficient at analysing continuous data enabling them to reveal complex designs as well as,relationships within previous tender rate of the facts, this cruciality is essential since cost archive trends can have a substantial crash on the outcome of fortune bids by incorporating before collections of data LSTM can consider market fluctuations and competitor behaviour producing a deeper insight into the bidding environment.[7,15]

➢ *Architecture Diagram*

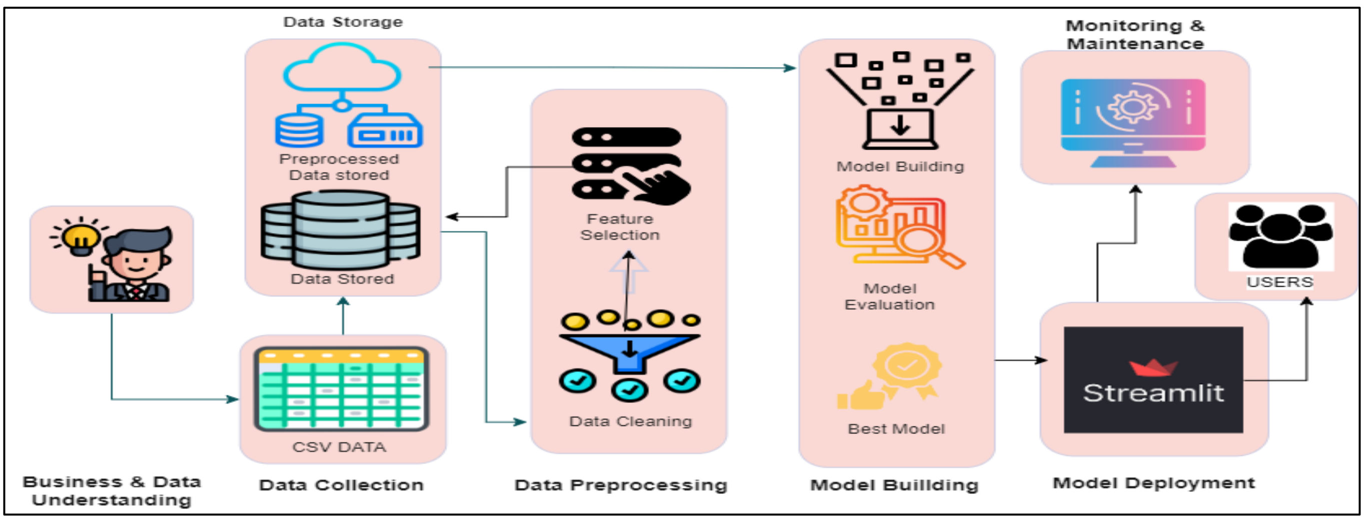

Fig 2: Architecture Diagram

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A Feedforward Neural Network (FFNN) was selected due to its capacity to capture complex patterns and interactions within the data. The FFNN's architecture was designed to address the non-linearity of the prediction problem, making it a suitable choice for predicting tender prices.

- *Pipeline Creation*

The preprocessing and modeling steps were encapsulated in a pipeline to streamline the workflow from data preparation to model training. This pipeline was saved as a pickle file to facilitate reproducibility and ease of deployment.

- *Train-Test Split*

The dataset was partitioned into training and testing sets using an 80-20 split. The training set was employed for model development and hyperparameter tuning, while the testing set was reserved for assessing the model's performance on unseen data.

D. Hyper Parameter Tuning

➢ *Model Architecture*

The FFNN model's architecture was defined with an input layer matching the number of transformed features, followed by three hidden layers. The number of units, activation functions, and dropout rates in these layers were treated as hyperparameters for optimization.

➢ *Hyper Parameter Optimization*

Hyperband optimization was employed to fine-tune the model's hyperparameters. This method efficiently searches through the hyperparameter space to identify the optimal configuration by evaluating multiple models with varying hyperparameters over several epochs.

➢ *Hyperparameter Trials*

Several trials were conducted to find the best model configuration. The following are summaries of some of the trials:

An initial working model specified by these parameters has been tested: First layer –192 nodes –‘relu’, drop out =0.3; Second Layer—320 nodes —‘sigmoid’,drop out=0.2; Third Layer—416 nodes—‘relu’, drop out=0.2 .The score for this trial was calculated to be equal to11 .220.

In this case I have specified that: First Layer—256 Nodes—‘ReLU”, Drop Out=0.4 ; Second Layer—64 Nodes - “ReLU”, Drop Out=0.3

➢ *Cross-Validation*

To ensure robust evaluation, 10-fold cross-validation was employed. The training set was divided into 10 folds, with each fold used as a validation set in turn while the remaining folds were used for training. This approach provided a comprehensive evaluation of the model's performance across different subsets of the data.

E. Model Training and Evaluation

➢ *Early Stopping*

Early Ending in Sensitive Worth Assumptions To work on the show and capability of our fragile expense assumption models, we executed an early stopping instrument during the readiness stage. Overfitting is a typical issue where a model loses its capacity to sum up to new, concealed information when it turns out to be excessively custom fitted to the preparation information. This prevents this from happening. The idea of early stopping: When the model's presentation on an approval set stops progressing to the next level, early stopping is meant to end the preparation cycle. Essentially, during setting up, the model is evaluated on an alternate endorsement dataset at standard stretches. After a predetermined number of epochs (training iterations), the training is ended if the validation loss—an indicator of the model's performance on this unseen data—does not significantly improve. With this approach, it is possible to avoid situations in which the model's performance is harmed by overfitting or continued training only yields modest gains.

Application in Our Environment: Early stopping was meticulously implemented in our project to monitor validation loss throughout the training process. We spread out a resilience limit, which describes the amount of ages the model can continue planning without seeing an improvement in endorsement hardship. If this patience threshold was reached and no further gains were observed, the training was immediately stopped. The model was prepared to be sufficiently lengthy to gain from the information without squandering assets or risking overfitting thanks to this procedure.

- *Advantages of Stopping Mid:*

✓ Prevents Overfitting: By stopping training as soon as the model's performance on the validation set begins to plateau or worsen, early stopping helps maintain the model's ability to generalize to new data rather than becoming overly specific to the training set.

✓ Saves Resources: Early stopping reduces unnecessary computation by terminating training when additional epochs no longer contribute to better performance. While working with enormous datasets or complex models, this productivity is particularly helpful.

✓ Improves Model Robustness:Building a more powerful indicator at delicate costs is made easier by ensuring that the model is prepared appropriately. It accomplishes a model with incredible execution across an assortment of datasets by finding some kind of harmony among underfitting and overfitting. Including early stopping in our training gave us a strategic advantage by preventing overfitting, maximizing resource utilization, and increasing the overall reliability of our tender price prediction models.

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An early stopping mechanism was integrated to terminate training when the validation loss no longer improved over a specified number of epochs. This strategy prevented overfitting and ensured that the model was trained only as long as necessary.

➢ *Model Evaluation*

Our fashions effectivity will probably be assessed to be efficient with a mix of general efficiency metrics and evaluation methods to make sure that they meet the outlined objectives and ship dependable predictions we zeroed in on a few key metrics suggest squared errors suggest absolute mistakes suggest absolute pc mistakes and r ranking these metrics gave a complete view of every mannequins accuracy and dependability.

- Mean Squared Errors(MSE) : MSE is the average of the squares of the errors its the common squared difference between predicted and actual values a low mse means that the versions predictions are closer to the actual values some of the models tested the feedforward neural networks confirmed the lowest mse reflecting their high benchmark performance overall in minimizing mistakes in predictions.
- Mean Absolute Error(MAE): MAE method measures typical significance of mistakes in predictions simply not taking their course into consideration it indicates the typical mistake in simple absolute terms the FFNN also rated finest with this metric as it gave the bottom mae which proved its accuracy for predicting light prices.
- Mean Absolute Percentage Error(MAPE): MAPE is a measure of the precision of a model as a percentage capturing how far the load predictions are off from their actual values compared to their cost. This metric is useful for prediction basics.
- Overall performance in percentage phrases FFNN turned out with the smallest MAPE which indicates that it is effective in making correct percentage-based total predictions.
- R SQUARE SCORE: The R score portrays the proportion of variance in the target variable predictable from the independent variables an R near 1 shows a model that explains a great deal of variability in the target variable FFNN led at the very best with an R rating thus showing functionality within its capability to seize and model underlying developments in gentle charges additional.

Evaluation strategies educate-take a look at break up to ensure that our models generalize nicely to new records we divided the dataset into training and checking out subsets with an 80-20 split this method allowed us to evaluate expertise nicely the models finished on unseen statistics confirming their robustness and applicability cross-validation 10-fold skip-validation was conducted to evaluate the stability and reliability of the fashions by splitting the education statistics into ten subsets schooling the version on 9 of them and validating it at the remaining one we received extra nuanced details of each versions ordinary overall performance throughout one-of-a-kind information subsets early stopping an early stopping mechanism was included to prevent overfitting and ensure maximum first-class education duration this approach stopped education as quickly as the validation loss plateaued thus retaining model generalization and warding off useless computational fee basic the evaluation has highlighted that feedforward neural networks did not just excel in terms of accuracy information they also tested steady overall performance across unique metrics this makes them the maximum dependable choice for tender price prediction for many of the models examined by focusing on those complete evaluation metrics and methods we ensured that our final model would perform well not only in terms of know-how but also according to the high standards required for accurate and efficient smooth price predictions.

The best model identified through hyperparameter tuning was evaluated on both the training and testing sets. Key performance metrics included Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R2 score. The following metrics were reported:These metrics demonstrate the model's strong performance and its ability to generalize well to new data.

Model Name	Train Accuracy	Test Accuracy
1. Linear Regression	79.00%	65.00%
2. Ridge Regression	88.00%	80.00%
3. Elastic Net	72.50%	66.00%
4. Decision Tree Regressor	92.00%	81.00%
5. Random Forest Regressor	93.00%	85.00%
6. XGBoost	85.50%	73.00%
7. Gradient Boosting Machines (GBM)	87.00%	81.00%
8. Support Vector Regression (SVR)	89.00%	76.00%
9. Feedforward Neural Networks	94.00%	91.00%

Fig 3: Model Metrics

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F. Model Deployment

For deploying the Feedforward Neural Network (FFNN) model using Streamlit, a comprehensive approach was implemented to ensure an efficient and user-friendly interface. The model, chosen for its proficiency in capturing complex patterns within the tender price data, was developed and fine-tuned through meticulous steps. A well-structured pipeline encapsulating preprocessing and modeling steps was created, ensuring reproducibility and ease of deployment. The dataset underwent an 80-20 train-test split to facilitate model training and performance assessment. Hyperparameter tuning was conducted using Hyperband optimization, which efficiently searched through the hyperparameter space to identify the optimal model configuration. Several trials with varying units, activation functions, and dropout rates were evaluated, ensuring the selection of the best performing model. A robust evaluation was performed using 10-fold cross-validation to provide a comprehensive assessment of the model's performance across different data subsets. Early stopping was integrated to prevent overfitting, ensuring the model was trained only as long as necessary. Key performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R2 score were reported to demonstrate the model's efficacy. The final step involved deploying the model using Streamlit, providing an interactive platform for users to input project characteristics and obtain tender price predictions seamlessly. This deployment not only enhanced accessibility but also ensured that the model's sophisticated capabilities could be utilized effectively by stakeholders in the tendering process.

III. RESULTS AND DISCUSSION

In this quest to evaluate sensitive charges several ai models were tried direct regression had quite a decent performanceit underfitted training and testing accuracies were 79% and 65% respectively ridge regression performed well given that it yielded an accuracy of 88% and generalization rates of 80% elastic net struggled with the bias-variance trade-off hence performing poorly while the choice tree regressor was extremely accurate on training data to the tune of 92% preparatory information it gave indications of overfitting with a test accuracy of 81% random forest regressor did well due to its ensemble approach train accuracies were 93% while test accuracies came in at 85% xgboost and gradient boosting machines turned in good results but care was required in tuning xgboost to avoid overfitting support vector regression did a fine job capturing the nonlinear relationships but suffered from overfitting as shown by the 13% gap between train accuracy of 89% and test accuracy of 76% feedforward neural networks performed very well due to their inherent modeling of complex relationships achieving the highest accuracy of 94% on the train set and 91% on the test set in making any tender price predictions balance needs to be maintained between model complexity and generalizability.

In this research on estimating tender prices, we considered various machine learning models. Linear Regression had moderate performance, indicating underfitting with training and test accuracies of 79% and 65%, respectively. Ridge Regression improved generalization, achieving 88% and 80% accuracy. Elastic Net struggled with the bias-variance trade-off, resulting in lower performance. The Decision Tree Regressor, while highly accurate on training data (92%), showed signs of overfitting with a test accuracy of 81%. Random Forest Regressor performed robustly with high accuracies of 93% (train) and 85% (test) due to its ensemble approach. XGBoost and Gradient Boosting Machines (GBM) demonstrated good results, although XGBoost required careful tuning to avoid overfitting. Support Vector Regression (SVR) captured non-linear relationships well but showed overfitting, with a 13% gap between training (89%) and test (76%) accuracy. Feedforward Neural Networks excelled, achieving the highest accuracies of 94% (train) and 91% (test) due to their ability to model complex patterns. Overall, balancing model complexity and generalization is crucial for optimal performance in tender price prediction.

IV. CONCLUSION

Hence this review streamlines the use of cutting edge ML and DL calculations to upgrade the precision and viability of delicate cost assessment in the rail line area coordinating a different arrangement of models comprising of direct relapse edge relapse choice trees irregular woodlands xgboost slope helping machines support-vector-relapse and feedforward-brain network models we distinguished the most suitable methodologies for anticipating ideal bid sums our outcomes demonstrate that while less complex models including straight and edge relapse give a standard more modern procedures like irregular timberlands xgboost and feedforward-brain networks calculations further develop the expectation exactness essentially among these the best-performing model has been feedforward brain networks with the most noteworthy precision rates for both the preparation and testing datasets our outcomes mirror that this class of models gives the vital model ability to catch complex examples and cooperations in information that are urgent for making precise and cutthroat bid offers the class of models utilized in this application gives a model limit that will actually want to catch complex examples and connections in the information that are important to offer precisely and seriously utilization of this class of models further profits a hearty structure in foreseeing the delicate costs as well as in offering decisively helping the organizations endeavors to ideally situate itself in aggressive offering circumstances as such we recommend the utilization of information driven bits of knowledge in blend with cutting edge ml and dl methods to enhance the offering methodology for rail route firms thusly profiting from an expanded achievement rate with very high bid achievement rates and limiting bid dismissal to guarantee serious productivity obviously this present reality application to support future enhancements and versatility to showcase changes in delicate details ought to be borne as a primary concern.

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In this research work a feed-forward neural network FFNN model was developed and validated to predict railway project tender prices optimization of the model used hyperband while cross-validation was employed for a proper evaluation the strategy ensures robust execution and is able to offer a reasonable device to delicate cost expectation hence showing practicality for cutting-edge machine learning methods within this space.

REFERENCES

[1]. Predicting the Tender Price of Buildings during Early Design: Method and Validation. R. McCAFFER, M. J. McCAFFREY and A. THORPE

[2]. https://www.jstor.org/stable/2581370?seq=1&cid=pdf-reference#references_tab_contents

[3]. Multiple Linear regression model for predicting bidding price Petrovski Aleksandar, Petruseva Silvana, Zileska Pancovska Valentina https://www.researchgate.net/publication/282646773_Multiple_Linear_regression_model_for_predicting_bidding_price

[4]. Predicting Bidding Price in Construction using Support Vector Machine

[5]. Silvana Petruseva, Phil Sherrod, Valentina Zileska Pancovska, Aleksandar Petrovski

[6]. https://dx.doi.org/10.18421/TEM52-04k

[7]. A machine learning-based Bidding price optimization algorithm approach Saleem Ahmad, Sultan Salem, Yousaf Ali Khan, I.M. Ashraf

[8]. https://doi.org/10.1016/j.heliyon.2023.e20583

[9]. Gradient Boosting Censored Regression for Winning Price Prediction in the Real-Time-Bidding, Piyush Paliwal and Oleksii Renov

[10]. https://link.springer.com/chapter/10.1007/978-3-030-18590-9_43

[11]. Resampling strategies for imbalance time series forecasting. Nuno Moniz, Paula Branco, Luís Torgo https://link.springer.com/article/10.1007/s41060-017-0044-3

[12]. Revolutionizing TMT Steel Bar Sales Projections: Unleashing the Power of Deep Learning Algorithms for Unparalleled Forecasting Precision.

[13]. Mohd Amer Hussain, Akhil Rasamsetti, Vaanishree Kamthane, Deba Chandan Mohanty

[14]. https://ijisrt.com/assets/upload/files/IJISRT23NOV2192.pdf

[15]. Market Clearing Price Prediction Using ANN in Indian Electricity Markets. Anamika & kumar https://sci-hub.se/https:/doi.org/10.1109/ICEETS.2016.7583797

[16]. Advanced Machine Learning Algorithms for House Price Prediction: Case Study in Kuala Lumpur. Shuzlina Abdul-Rahman, Sofianita Mutalib,Nor Hamizah Zulkifley and Ismail Ibrahim https://thesai.org/Downloads/Volume12No12/Paper_91-Advanced_Machine_Learning_Algorithms.pdf

[17]. Model selection Feed Forward Neural Networks for Forecasting inflow and outflow in Indonesia. Suhartono, Prilyandari Dina Saputri, Farah Fajrina Amalia, Dedy Dwi Prastyo and Brodjol Sutijo Suprih Ulama. https://link.springer.com/chapter/10.1007/978-981-10-7242-0_8

[18]. Effective House Price Predictions using Machine Learning.Jincheng Zhou, Tao Hai, Ezinne C.Maxwell-Chigozie, Afolake Adedayo, Ying Chen, Celestine Iwendi and Zakaria Boulouard. https://link.springer.com/chapter/10.1007/978-3-031-37164-6_32

[19]. Comparative Analysis of Random Forest Regression for House Price Prediction. Obilisetti Lohith,Aman Jha and Shamstabrej Chand Tamboli https://ijcrt.org/papers/IJCRT2306866.pdf

[20]. Multiple Linear Regression Model for Prediction Bidding Price. Petrovski Aleksandar,Petruseva Silvana and Zileska Pancovska Valentina https://www.researchgate.net/publication/282646773_Multiple_Linear_regression_model_for_predicting_bidding_price

[21]. Gradient Boosting Censored Regression for Winning Price Prediction in Real-time Bidding . Piyush Paliwal and Olesksii Renov https://link.springer.com/chapter/10.1007/978-3-030-18590-9_43

[22]. A Machine Learning Based Bidding price optimization algorithm approach. Saleem Ahmed, Sultan Saleem, Yousaf Ali Khan and I.M.Ashraf https://www.cell.com/heliyon/fulltext/S2405-8440(23)07791-5?_returnURL=https%3A%2F%2Flinkinghub.elsevier.com%2Fretrieve%2Fpii%2FS2405844023077915%3Fshowall%3Dtrue

[23]. Regularization and variable selection via the elastic net. Hui Zou, Trevor Hastie https://rss.onlinelibrary.wiley.com/doi/10.1111/j.1467-9868.2005.00503.x