

**Phase-2**

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**Github Repository**   
**Link:https://github.com/dharaniM4/Dharani-M-naan-mudhalvan.git**

**1. Problem Statement**

●*Accurately forecasting house prices is crucial for buyers, sellers, and real estate investors to make informed financial decisions. The challenge lies in capturing the complex, non-linear relationships among numerous variables like location, size, amenities, and economic conditions.*

●*Type of Problem: Regression (predicting a continuous variable house price).*

●*Why It Matters: Enhances decision-making in real estate markets, supports*  *financial institutions in loan processing, and aids urban planning initiatives.*

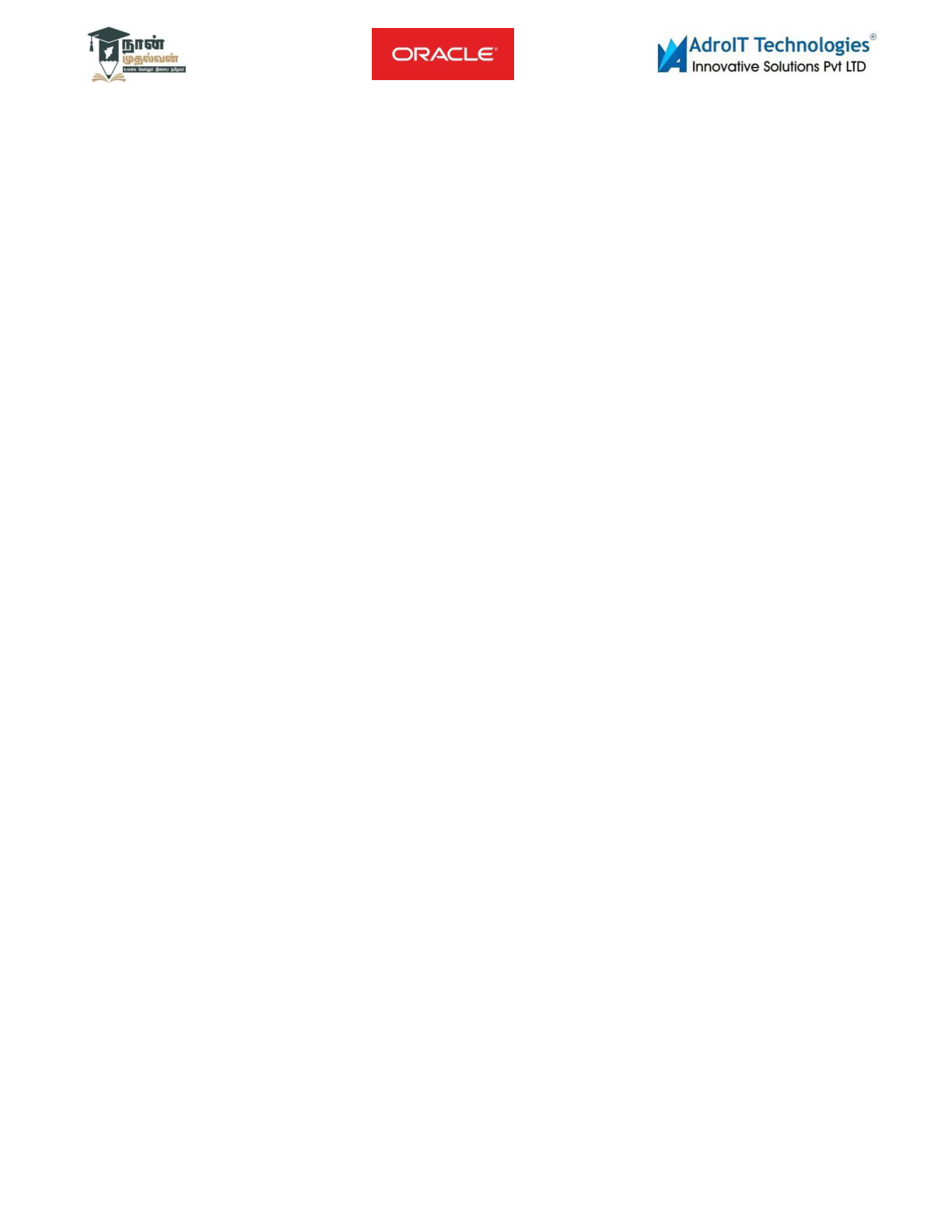
**2.Project Objectives**

●*Primary Goal: Develop a robust, interpretable, and accurate regression*  *model for house price prediction.*

●*Technical Objectives:*

●*Analyze the dataset to identify significant predictors.*

●*Compare multiple regression techniques.*



●*Optimize performance using feature engineering and hyperparameter tuning.*

●*Updated Goal: After initial EDA, emphasis shifted to improving model interpretability while retaining accuracy due to multicollinearity in features.*

●*Assess model fairness and bias, ensuring that the model does not*   
 *systematically underpredict or overpredict based on location or house type.*

●*Updated Focus: After initial EDA, emphasis shifted toward improving model interpretability while maintaining accuracy, due to multicollinearity observed among features.*

**3.Flowchart of the Project Workflow**

1. Data Collection   
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2. Data Preprocessing   
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3. Exploratory Data Analysis (EDA)   
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4. Feature Engineering   
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5. Model Building   
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6. Evaluation   
 ↓   
7. Visualization   
 ↓   
8. Conclusion

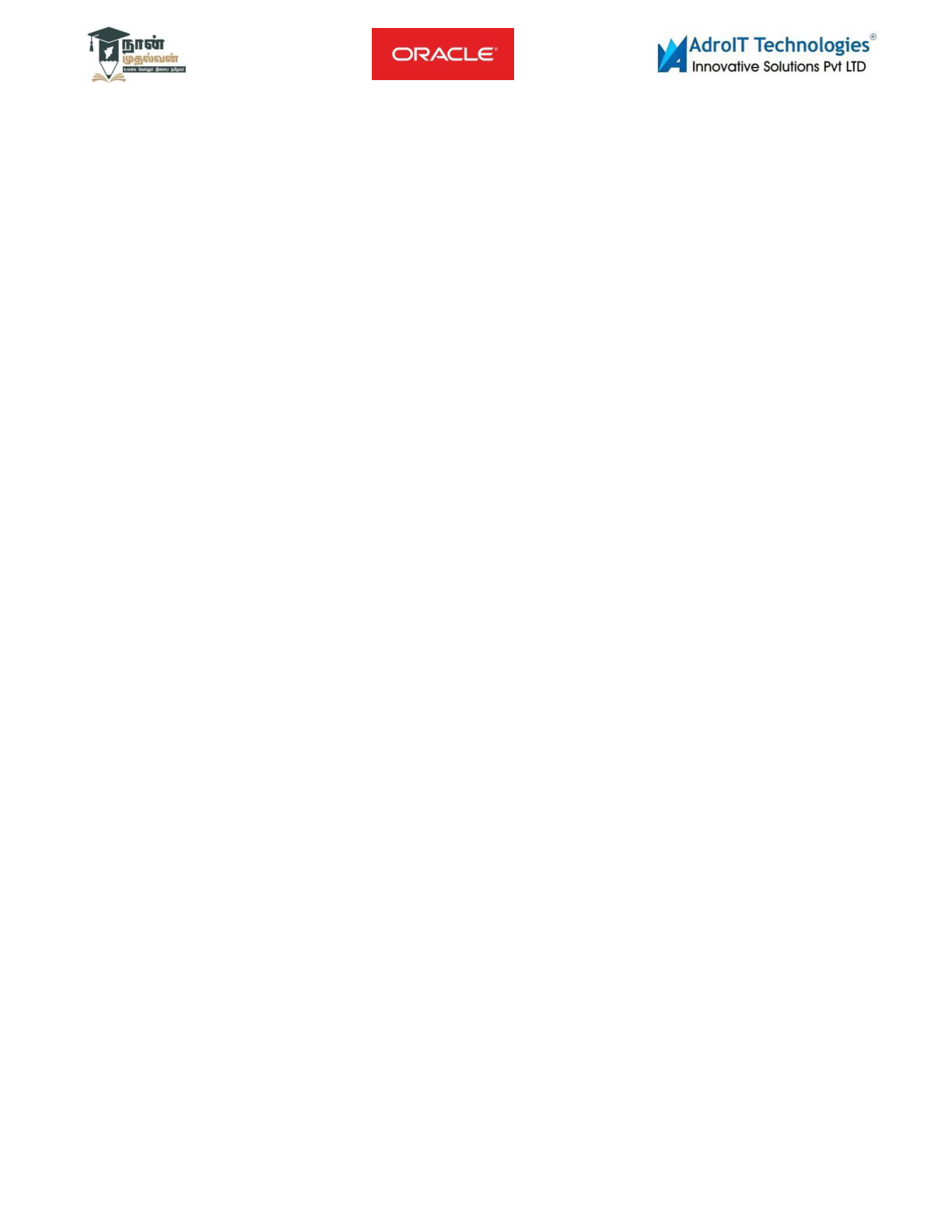
**4.Data Description**

●*Source:Kaggle – House Prices: Advanced Regression Techniques*

●*Type: Structured data (tabular)*

●*Records & Features: ~1460 rows, 80+ features*

●*Dataset Nature: Static*



●*Target Variable: SalePrice*

**5.Data Preprocessing**

●*Handled missing values using mean/median or domain-specific logic.*

●*Removed duplicate records and verified unique identifiers.*

●*Detected outliers using IQR and visual methods (boxplots).*

●*Converted categorical columns to numerical using one-hot encoding.*

●*Standardized numeric features using StandardScaler.*

●*Ensured data types were consistent across columns.*

**6.Exploratory Data Analysis (EDA)**

●*Univariate Analysis:*

○*Used histograms and boxplots for numeric features.*

●*Bivariate/Multivariate Analysis:*

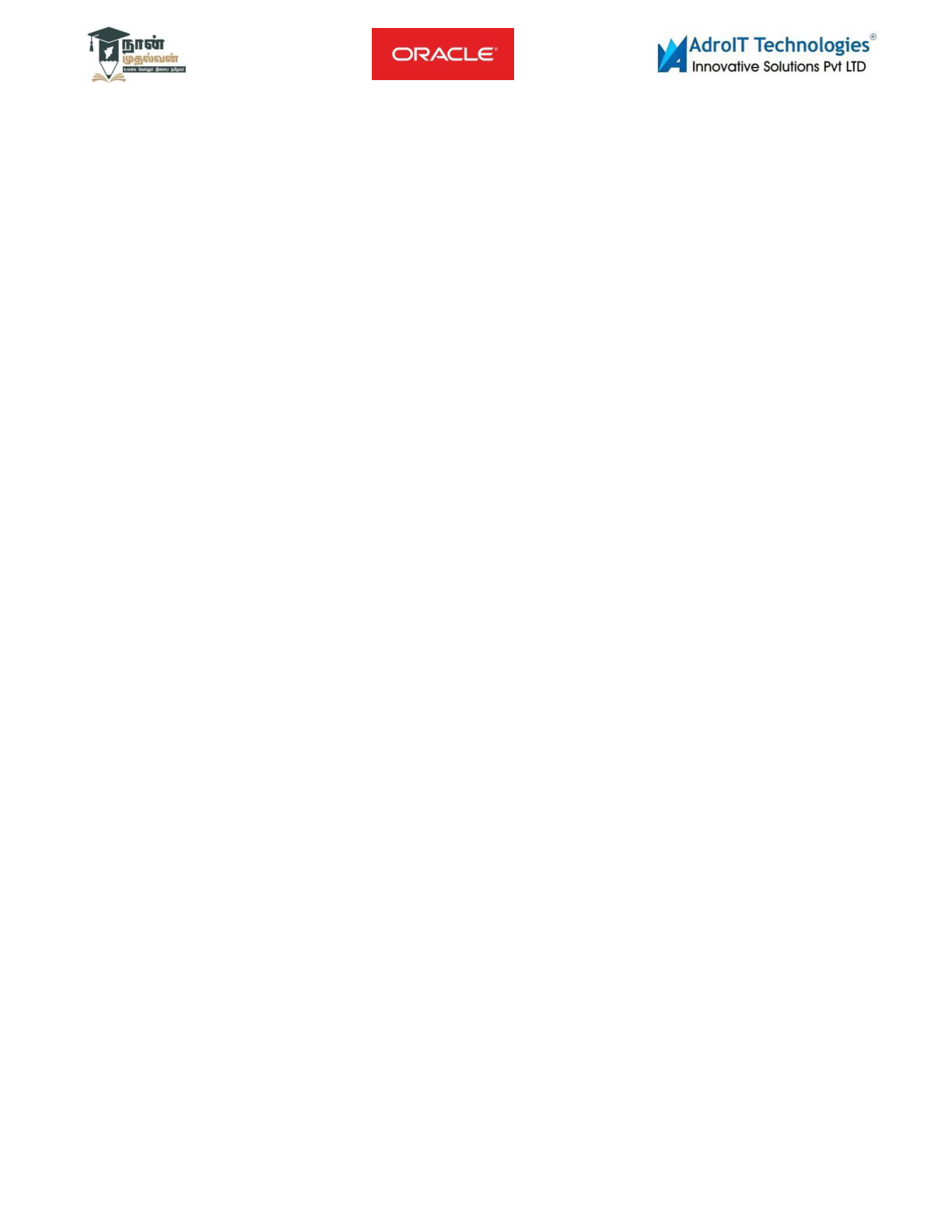
○*Correlation matrix and pair plots for key variables vs. Sale Price.*

●*Insights Summary:*

○*Strong positive correlation with features like Overall Qual,*

*GrLivArea.*

○*Location (Neighborhood) plays a major role.*



○*Some features are highly skewed and need transformation.*

**7.Feature Engineering**

●*Created new features such as “Total Bathrooms”, “House Age”, and “Is*  *Remodeled”.*

●*Applied log transformation on skewed features.*

●*Binned continuous variables (e.g., Year Built into decades).*

●*Removed features with high collinear or low variance.*

●*Created interaction terms (e.g., OverallQual \* GrLivArea) to capture*  *combined effects.*

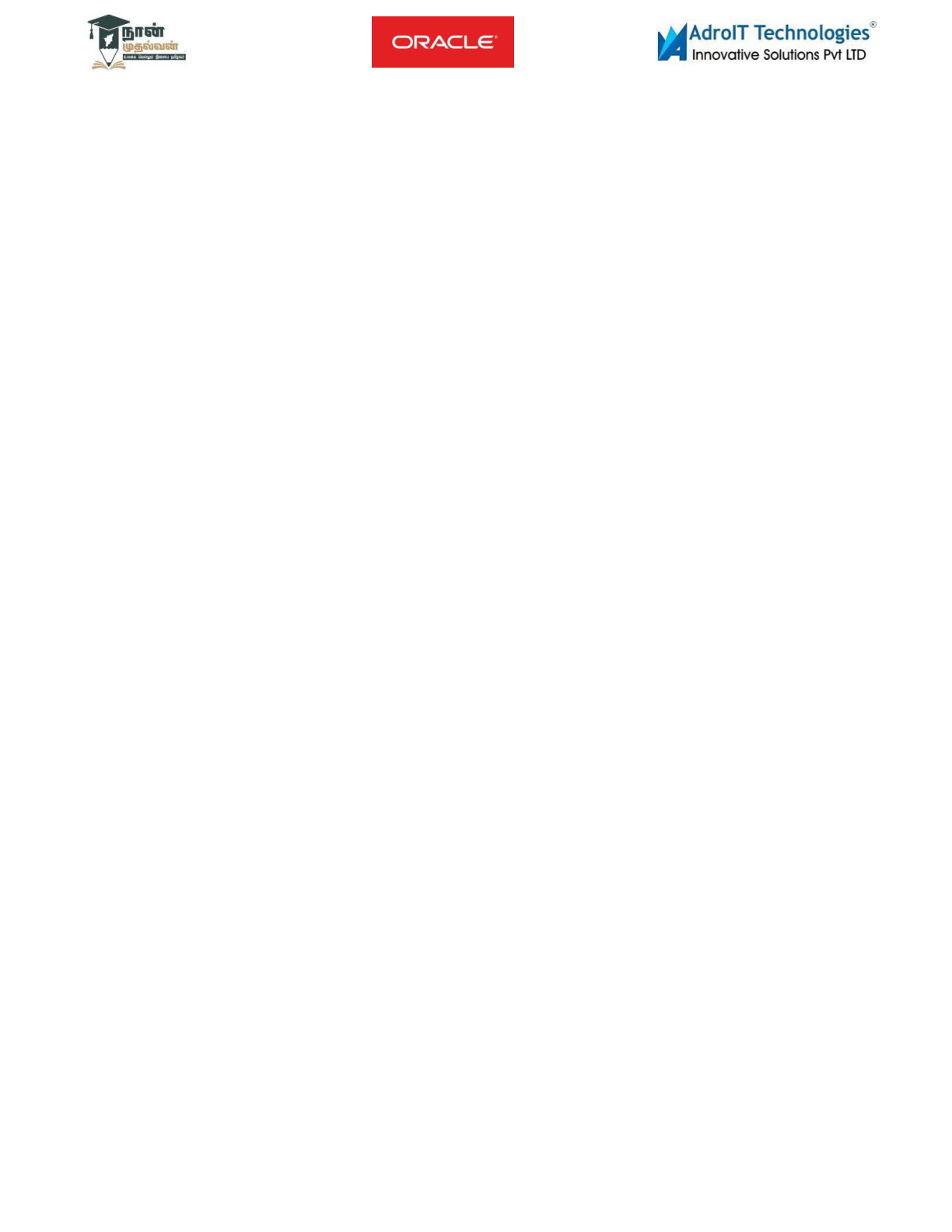
●*Introduced polynomial features for important variables like GrLivArea to*  *model non-linear patterns.*

**8.Model Building**

●*Choice of Models: Selected Linear Regression for baseline interpretability and Random Forest Regressor for handling non-linear relationships and feature interactions.*

●*Data Split: Divided the dataset into 80% training and 20% testing sets to evaluate model generalization performance. Stratification was not required for continuous target variables.*

●*Evaluation Metrics: Used MAE, RMSE, and R² Score to objectively compare*  *models' accuracy and reliability for regression tasks.*



●*Performance Observation: Random Forest outperformed Linear Regression by achieving lower error values and a higher R² score, showing better ability to model complex patterns in the data.*

*○*  *E.g., Logistic Regression, Decision Tree, Random Forest, KNN, etc.*

●*Applied cross-validation (k-fold) to validate the robustness of model*  *performance.*

●*Performed Grid Search for Hyperparameter Tuning (e.g., tuning number of*  *trees, max depth in Random Forest).*

**9.Visualization of Results & Model Insights**

●*Feature Importance Plot: Identified top predictors like OverallQual,*  *GrLivArea, and GarageCars.*

●*Residual Plots: Random Forest had more uniformly distributed residuals.*

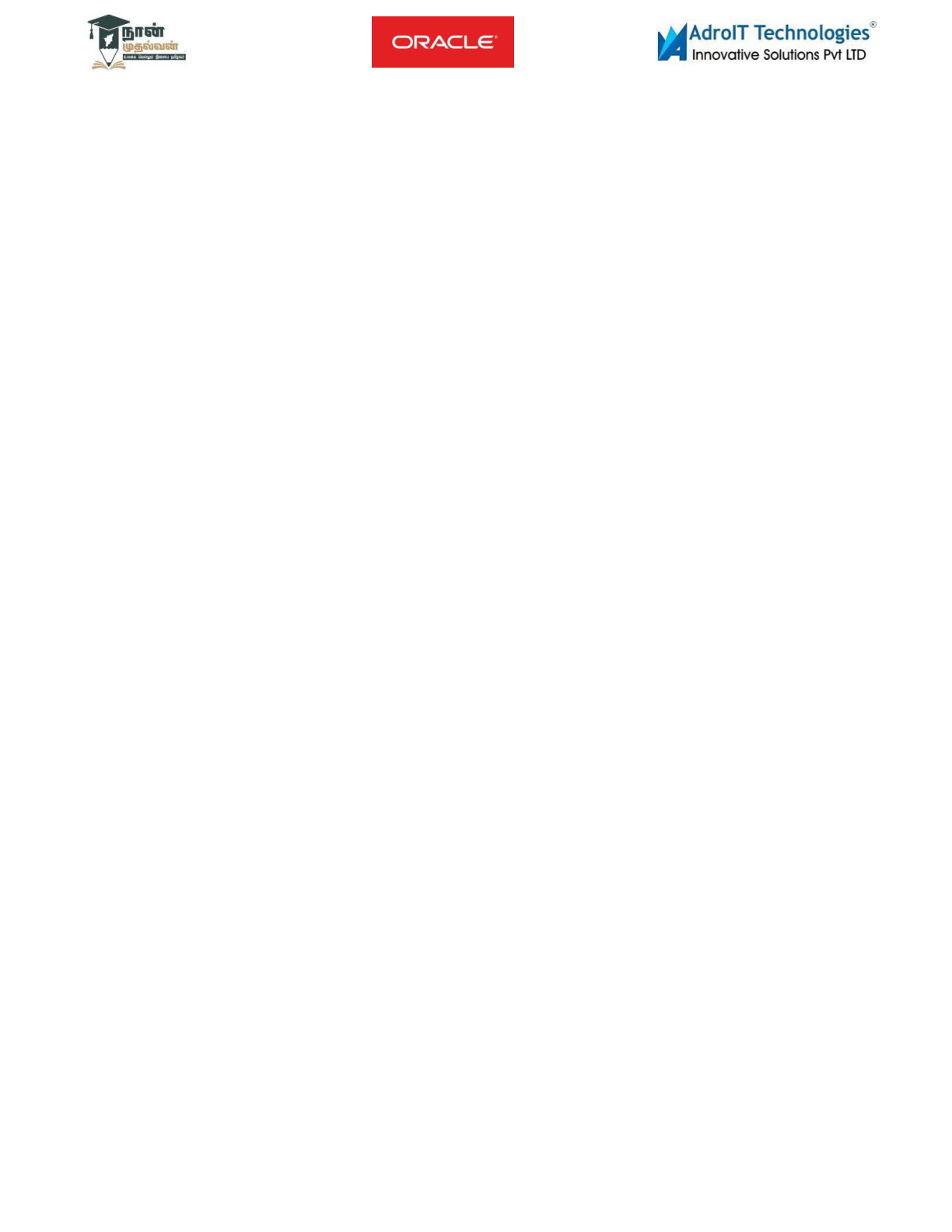
●*Model Comparison: Visualized performance using bar plots for RMSE and*  *R².*

●*Actual vs Predicted Plot:*

*°Scatter plot comparing predicted SalePrice vs. actual SalePrice, highlighting model accuracy visually.*

●*Distribution of Prediction Errors:*

*°Plotted histogram of residuals to check for any bias or skewness in predictions*



**10.Tools and Technologies Used**   
 ●*Language: Python*

●*IDE: Google Colab*

●*Libraries: pandas, numpy, matplotlib, seaborn, scikit-learn, XGBoost*

●*Visualization Tools: matplotlib, seaborn, Plotly*

**11.Team Members and Contributions**

1) J.Ayisha banu: Data cleaning and documentation. 2) S.Anusiya:

EDA and problem objective.

3) M.Dharani: Feature engineering and reporting.

4) M.Kaviya: Model development and visualization of results.