AI in Business Decision-Making: Using machine learning algorithms to assist managerial decision

Authors

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Abstract

Businesses are operative because of the mixture of Artificial Intelligence (AI) into decision-making measures. Using predictive analytics, automation, and optimization as a main effort, this training can examine the use of the machine learning algorithms to providing the management decision-making. Businesses can re-establish the predicted outcomes similarly can spot trends in large volumes of data and estimate them with the help of machine learning models. Managers may reduce the risks factors and allocate resources optimally and make well-informed decisions leveraging these tools.

Similarly, this research examines hands-on applications in some fields, including finance, marketing, and supply chain management, wherever machine learning methods have been applied to enhance decision-making efficiency. The algorithms are mainly comprising the decision trees, random forests, and the neural networks.

The results show that AI has a great agreement of possible to convert management decision-making into a competitive corporate setting by refining speed and accuracy.

1. Introduction

In today's rapidly evolving business landscape, decision-making has become increasingly complex due to the overwhelming availability of data. Businesses have to continuously strive to maintain competitive edge, thus it has become increasingly critical to derive actionable insights from data. AI through machine learning algorithms has become a powerful tool in enabling businesses to process huge amounts of data and make better informed decisions with precision and speed.

For example, we can consider Amazon, which is world's largest e-commerce platform, using AI and machine learning algorithms for demand forecasting enabling it to optimize inventory management and lower costs by up to 10% *(Bose & Mahapatra, 2018)*. Similarly, JPMorgan has employed AI to improve fraud detection, saving millions in potential losses annually *(Marr, 2019).*

Machine learning allows you to learn from historical data and make predictions without requiring any explicit programing. This has transformed managers' decision-making approach as they get better insights, they can optimize operations and enhance strategic planning. Machine learning is empowering businesses to make better data-driven decisions in several streams from improving customer service using predictive analytics to automating supply chain decisions. They can make accurate decisions in a timely manner using this strategy.

Businesses striving to maintain a competitive edge must derive actionable insights from vast datasets. AI, through machine learning algorithms, has emerged as a powerful tool for enabling businesses to process large amounts of data and make more informed decisions with precision and speed. According to a report by McKinsey, companies that adopt AI in their operations are 20% more likely to outperform their competitors *(McKinsey & Company, 2018).*

This paper explores the application of machine learning algorithms to optimize key managerial decisions. In this paper, we will be discussing the following machine learning models Linear Regression, Polynomial Regression, Ridge Regression, Lasso Regression and Logistic Regression.

The challenge lies in using modern data analysis techniques to help managers in making more accurate, timely data-driven decisions. Machine learning algorithms have the potential to detect patterns, predict outcomes and automate decision processes. However, selecting an appropriate machine learning model and its application in real-world business scenarios remains a key issue for many businesses.

Problem Statement:

How can machine learning algorithms be effectively used to support managerial decision-making across various business functions, and what are the implications of adopting these technologies for improving decision accuracy, operational efficiency, and long-term business success?

Research Questions:

1. How can machine learning algorithms improve the accuracy and efficiency of managerial decision-making processes in businesses?
2. Which machine learning models (e.g., Decision Trees, Random Forest, Logistic Regression, SVM) are most effective for specific business functions, such as marketing, finance, or operations?
3. What are the primary challenges businesses face when adopting machine learning algorithms for decision-making, and how can these challenges be mitigated?
4. How does the integration of machine learning algorithms in decision-making affect long-term business performance and competitive advantage?
5. What is the impact of machine learning algorithms on reducing human biases in business decisions?

Literature Review:

The application of artificial intelligence (AI) and Machine Learning (ML) has gathered a lot of attention in recent years. Data in today's time is a vital asset for every organization. Thus, exploring ways in which AI can help enhance business decisions has become essential. This literature review explores the development, implementation and impact of machine learning algorithms focusing on improving decision-making.

Several studies have highlighted the potential of AI in business decision-making. *Davenport and Ronanki (2018)* emphasis that AI-driven decision-making allows businesses to process large datasets, making it possible to generate insights that were previously unachievable through traditional approaches. They argue that AI can restructure decision-making processes by predicting outcomes and recommending solutions, especially in areas like customer relations, inventory management, and financial forecasting.

Brynjolfsson and McAfee (2017) discuss how AI technologies can improve organizational decision-making by curtailing biases and improving the accuracy of predictions. They note that AI systems, when combined into decision frameworks, can reduce the uncertainty and inefficiencies essential in human-driven decision processes, thus allowing more effective strategy design and implementation.

Numerous machine learning models have been explored for their appropriateness in business decision-making. Decision trees, for instance, have been found to be highly understandable and valuable for managers who require clear explanations for predictions and recommendations *(Witten et al., 2016).* This model's simplicity and ability to visualize decision paths have made it popular for risk analysis, customer segmentation, and marketing strategies.

Random Forest, as highlighted by *Breiman (2001),* is an ensemble method that improves upon decision trees by combining the results of multiple trees to increase predictive accuracy and robustness. Studies have shown that Random Forests are particularly useful in high-stakes decisions, such as credit scoring and fraud detection, where accuracy is critical.

Logistic regression is another commonly used model, particularly for binary classification tasks. According to *Menard (2002),* logistic regression is widely applied in predicting customer churn, evaluating the likelihood of purchase, and assessing the success of marketing campaigns. Its popularity is attributed to its simplicity and interpretability in business contexts.

Support vector machines (SVM), as described by *Vapnik (1995),* have been applied successfully in decision-making tasks where clear separations between categories are needed. For instance, in financial decision-making, SVMs have been used to predict stock market trends and classify credit risks, demonstrating their efficacy in areas where decision boundaries are critical.

Research shows that AI and machine learning can improve managerial decision-making by improving efficiency and decision quality. According to *Shrestha, Ben-Menahem, and Krogh (2019)*, AI systems can assist managers by providing real-time data analysis, enabling faster decision-making while maintaining accuracy. Additionally, AI can help managers avoid cognitive biases that often affect human judgment, leading to more objective and data-driven decisions.

However, as noted by *Jarrahi (2018)*, while AI offers great potential for improving decision quality, there are challenges in the implementation of AI systems in managerial roles. The integration of AI into decision-making processes often requires substantial organizational change, including training managers to work effectively with AI systems and overcoming resistance to technology adoption.

Despite the potential benefits, there are notable challenges in the adoption of machine learning for business decision making. One of the main issues, as pointed out by *Ransbotham et al. (2018)*, is the lack of skilled personnel capable of deploying and managing AI systems. Furthermore, data quality and availability often pose significant hurdles. Organizations need to ensure that their data is not only vast but also clean, reliable, and relevant to the decision-making context.

Another critical challenge, as discussed by *Chen and Lin (2014),* is the interpretability of machine learning models. While some models, such as decision trees and logistic regression, offer clear explanations for their predictions, others like deep learning models often function as "black boxes," making it difficult for managers to understand how decisions are derived. This lack of transparency can hinder trust in AI-based decisions.

Various case studies have demonstrated the successful application of machine learning algorithms in business decision-making. For instance, Amazon's use of machine learning for demand forecasting and inventory management has allowed the company to optimize its supply chain and reduce costs *(Bose & Mahapatra, 2018).* In the financial sector, companies like JPMorgan have implemented AI to detect fraud and assess credit risks, improving operational efficiency and reducing human error *(Marr, 2019).*

Furthermore, companies in the retail sector have adopted machine learning models to enhance customer experience through personalized recommendations and targeted marketing. *McKinsey & Company (2018)* reports that businesses using AI for marketing decisions have seen increased customer satisfaction and revenue growth, demonstrating the value of machine learning in driving better business outcomes.

The literature review demonstrates that machine learning algorithms have the potential to revolutionize business decision-making by offering predictive insights, reducing human biases, and improving decision accuracy. Models like decision trees, random forests, logistic regression, and support vector machines are particularly useful for different business functions, including marketing, finance, and operations. However, challenges such as data quality, model interpretability, and organizational readiness must be addressed to fully realize the benefits of AI in managerial decisions.

Continued research on AI's application in business decision-making is crucial to address the ongoing challenges and to develop more robust, transparent, and effective AI-driven decision models for businesses across industries.

2. Methodology

The dataset used for this project consisted of 50,000 rows and 8 columns, with features such as 'carat', 'cut', 'color', 'clarity', and their respective ordinal values for diamonds, along with the 'price' as the target variable.

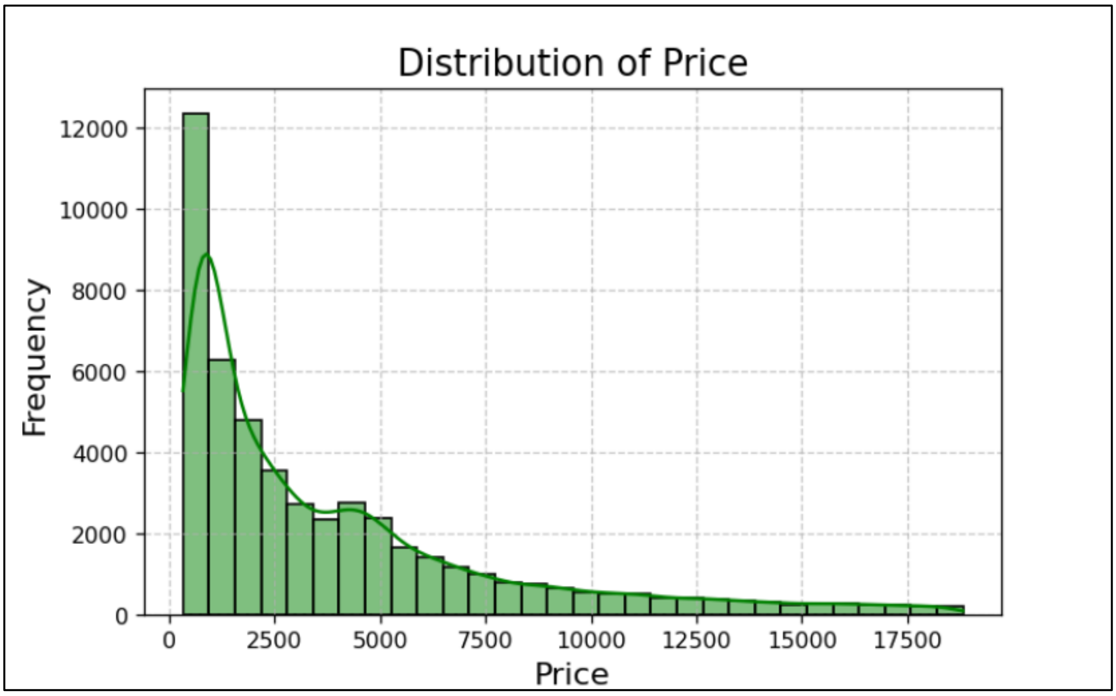

Figure 1. Distribution of Price

The price distribution is **right-skewed**, indicating that **most diamonds are priced in the lower range**. A large number of diamonds have prices concentrated around the lower to mid-range. Long tail extending to the right highlights that there are **some very expensive diamonds** in the dataset, which will be considered outliers. Most diamonds are moderately priced, with a few high-priced diamonds.

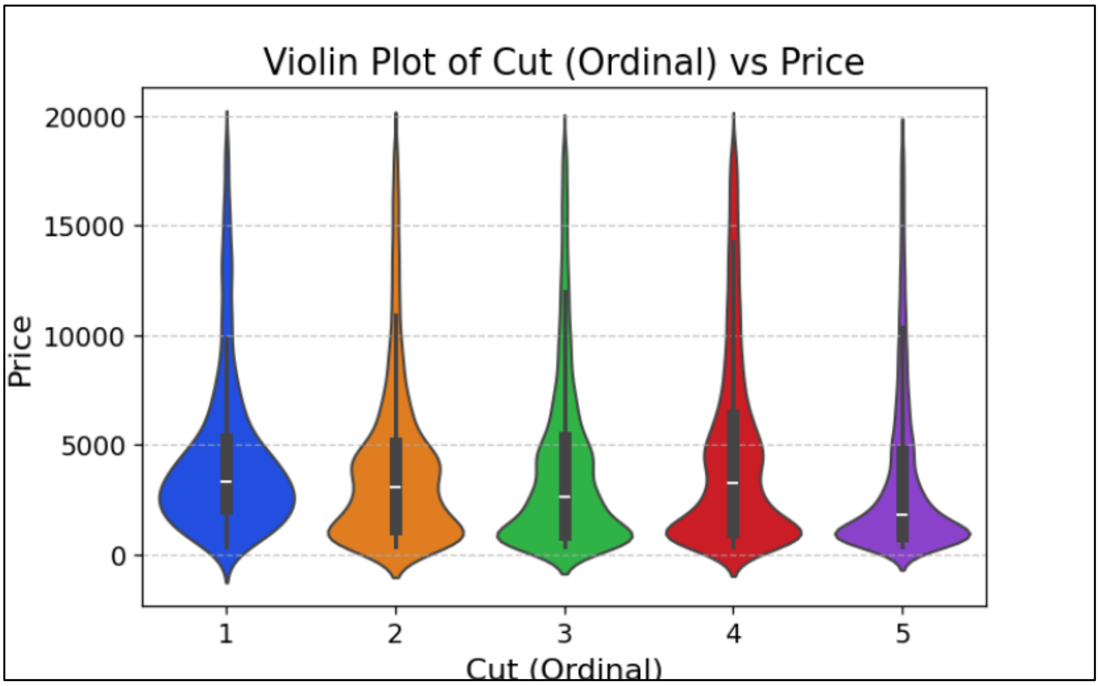

Figure 2. Violin Plot

The **Ideal cut** (represented by cut_ord=5 has a **broader and taller violin plot** in the higher price range, indicating that diamonds with an Ideal cut are generally **more expensive**. For lower cut qualities, such as cut_ord = 1 (Fair cut), the violin plot is **narrower and concentrated at lower prices**, meaning that **diamonds with lower cut quality are generally cheaper.** Diamonds with a Very Good cut (cut_ord = 3) exhibit a **broad price distribution** from lower to moderately higher prices, indicating significant variation within that cut category. Some cut_ord = 5 (Ideal cut) diamonds have **thin tails extending into the highest price ranges**, indicating that a few Ideal-cut diamonds are priced much higher than most.

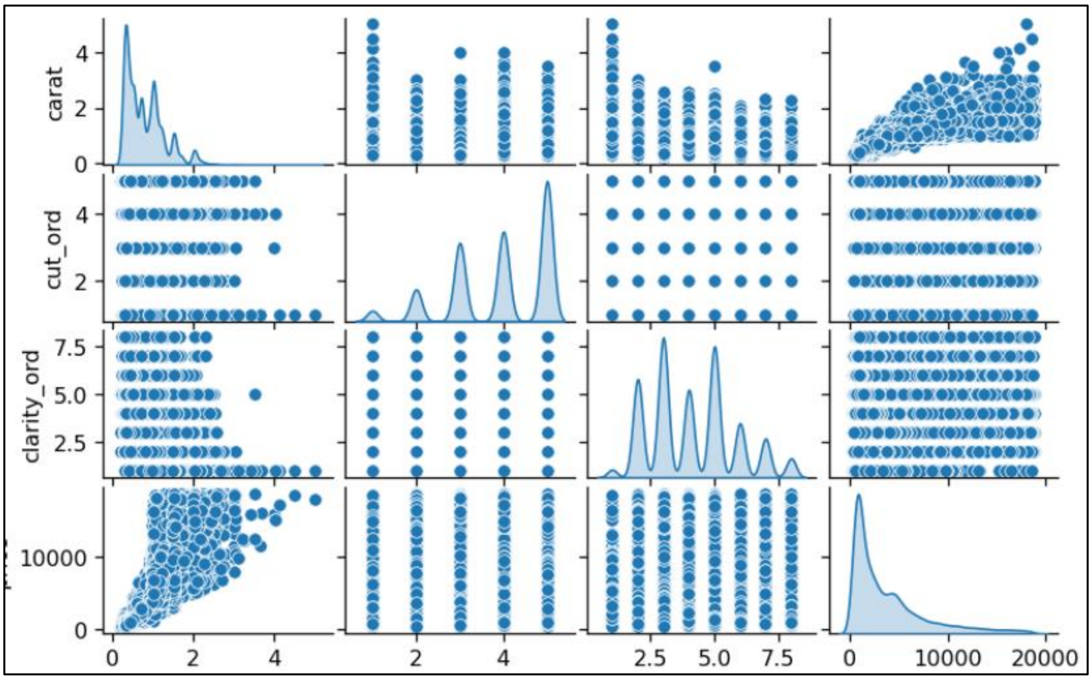

Figure 3. Scatter Plot

The scatter plot between carat and price shows a **strong positive correlation**. As carat weight increases, prices rise significantly. Larger diamonds (higher carat values) are typically much more expensive. Diamonds with carats greater than 1.5 tend to have much higher prices compared to smaller diamonds. The scatter plot between cut_ord and price shows a **weaker correlation** compared to carat, but still suggests that diamonds with better cuts (higher cut_ord values) tend to be more expensive. However, there is **more variability** in prices within the same cut category. Some diamonds with lower cut quality (e.g., cut_ord = 2) can still be relatively expensive, suggesting that other factors like carat may have more influence. The relationship between clarity and price is weaker, with more scattered points. This suggests that clarity does not have a strong impact on price when compared to carat or cut. Example: Diamonds with higher clarity (clarity_ord = 7) do not show a significant increase in price compared to those with moderate clarity. The distribution of carat shows that most diamonds in the dataset are **smaller**, and only a few are larger. This matches the right-skewed distribution seen in the price.

The methodology used in this research involved the application of multiple machine learning algorithms, each chosen based on its suitability for addressing specific business challenges.

Linear regression was chosen as the baseline model due to its ability to capture simple linear relationships between features and outcomes. This model is often used in forecasting sales or demand, where a straightforward relationship exists between variables like price and quantity sold.

Polynomial regression was chosen to address non-linear relationships within the data. For example, in pricing strategies, the relationship between certain product features (such as carat and price in the diamond industry) may not be linear, making polynomial regression an appropriate choice for enhancing predictive accuracy in such cases.

Ridge and lasso regression were chosen to avoid overfitting and perform feature selection, respectively. These models are critical in business contexts where large datasets with many variables are involved, such as customer segmentation or marketing optimization. By regularizing the models, we ensured that they generalized better to unseen data, thus providing more reliable predictions for decision-making.

Each model was carefully aligned with the business goal of improving decision accuracy, operational efficiency, and reducing risks in key areas such as marketing and financial forecasting.

Pre-processing Data:

The first step was to pre-process the data to ensure that only relevant information remained in the dataset. The categorical columns such as 'cut', 'color', and 'clarity' were converted into dummy variables using one-hot encoding. Non-relevant columns like 'Sr. No.' were dropped, while the key features—'carat', 'cut', 'cut_ord', 'color', 'clarity', and 'clarity_ord' were retained. The dataset was split into a training set (80%) and a testing set (20%) using the train_test_split function from Scikit-learn.

Machine Learning Algorithms:

- **Linear Regression**: This model was used as the baseline to assess the linear relationship between features and the target variable.

Linear Regression

```
{python}
# Linear Regression

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
lin_reg_predictions = lin_reg.predict(X_test)

# Evaluation
print("Linear Regression MSE:", mean_squared_error(y_test, lin_reg_predictions
))
print("Linear Regression R^2:", r2_score(y_test, lin_reg_predictions))
```

```
LinearRegression()
Linear Regression MSE: 1300636.7303636107
Linear Regression R^2: 0.9158942532453273
```

Figure 4. Linear Regression Model with code

- **Polynomial Regression**: To capture non-linear relationships, a degree-2 polynomial regression model was implemented.

Polynomial Regression

```
{python}
# Polynomial Regression

from sklearn.preprocessing import PolynomialFeatures

# Create polynomial features
degree = 2  # Set the degree of the polynomial
poly = PolynomialFeatures(degree=degree)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)

# Fit the Linear Regression model on polynomial features
poly_reg = LinearRegression()
poly_reg.fit(X_train_poly, y_train)

# Predictions
poly_predictions = poly_reg.predict(X_test_poly)

# Evaluation
mse = mean_squared_error(y_test, poly_predictions)
r2 = r2_score(y_test, poly_predictions)

# Display results
print("Polynomial Regression MSE:", mse)
print("Polynomial Regression R²:", r2)
```

```
LinearRegression()
Polynomial Regression MSE: 604742.4733982864
Polynomial Regression R²: 0.9608942942083364
```

Figure 5. Polynomial Regression Model with code

- **Ridge Regression**: Applied to avoid overfitting by adding L2 regularization.

Ridge Regression

```
{python}
# Ridge Regression

from sklearn.linear_model import Ridge

ridge_reg = Ridge(alpha=1.0)  # Adjust alpha as needed
ridge_reg.fit(X_train, y_train)
ridge_predictions = ridge_reg.predict(X_test)

# Evaluation
print("Ridge Regression MSE:", mean_squared_error(y_test, ridge_predictions))
print("Ridge Regression R^2:", r2_score(y_test, ridge_predictions))
```

```
Ridge()
Ridge Regression MSE: 1300566.1602876715
Ridge Regression R^2: 0.9158988166632263
```

Figure 6. Ridge Regression Model with code

- **Lasso Regression**: Similar to Ridge, but with L1 regularization for feature selection.

Lasso Regression

```
{python}
# Lasso Regression

from sklearn.linear_model import Lasso

lasso_reg = Lasso(alpha=1.0)  # Adjust alpha as needed
lasso_reg.fit(X_train, y_train)
lasso_predictions = lasso_reg.predict(X_test)

# Evaluation
print("Lasso Regression MSE:", mean_squared_error(y_test, lasso_predictions))
print("Lasso Regression R^2:", r2_score(y_test, lasso_predictions))
```

```
Lasso()
Lasso Regression MSE: 1299743.8320066174
Lasso Regression R^2: 0.915951992567413
```

Figure 7. Lasso Regression Model with code

Model Tuning and Evaluation:

- **Metrics**: Each model was evaluated based on Mean Squared Error (MSE) and R-squared (R^2) metrics to measure prediction accuracy and goodness of fit.

- **Hyperparameter Tuning**: For Ridge and Lasso regressions, the alpha parameter was tuned to balance regularization strength.

3. Results

Table 1. Results of Regression Models

Model	MSE	R^2
Linear Regression	1,300,915.58	0.9158
Polynomial Regression	604,729.87	0.9609
Ridge Regression	1,300,566.16	0.9159
Lasso Regression	1,299,743.83	0.9160

Polynomial Regression achieved the best results with an R^2 of 0.9609, indicating that non-linear patterns significantly improve predictions. Ridge and Lasso provided similar results to linear regression, but with slightly better generalization due to regularization.

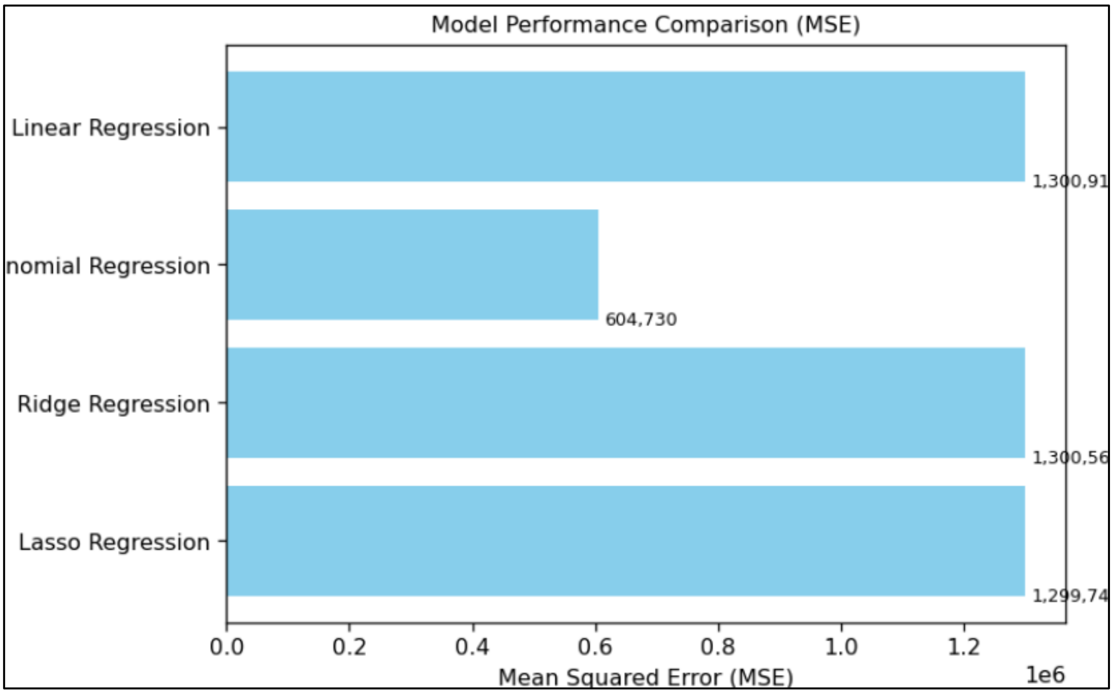

Figure 8. MSE Plot (Mean Squared Error comparison for models)

Polynomial Regression has the **lowest MSE** value of **604,729.87**. This indicates that it provides the best fit for the data among the models tested, suggesting that it captures the underlying patterns more effectively than the other models. **Linear Regression** and **Ridge Regression** exhibit significantly higher MSE values (**1,300,915.58** and **1,300,566.16**, respectively). This indicates that these models do not fit the data as well, and their predictions are less accurate compared to the Polynomial Regression model. **Lasso Regression** has an MSE of **1,299,743.83**, which is slightly better than Linear and Ridge Regression but still falls short of the performance of Polynomial Regression. The higher MSE values for Linear and Ridge Regression suggest potential **underfitting**—indicating that these models might be too simple to capture the complexity of the relationship between features and the target variable (price). The **lower MSE of Polynomial Regression** highlights the importance of selecting a more complex model when dealing with non-linear relationships in the data.

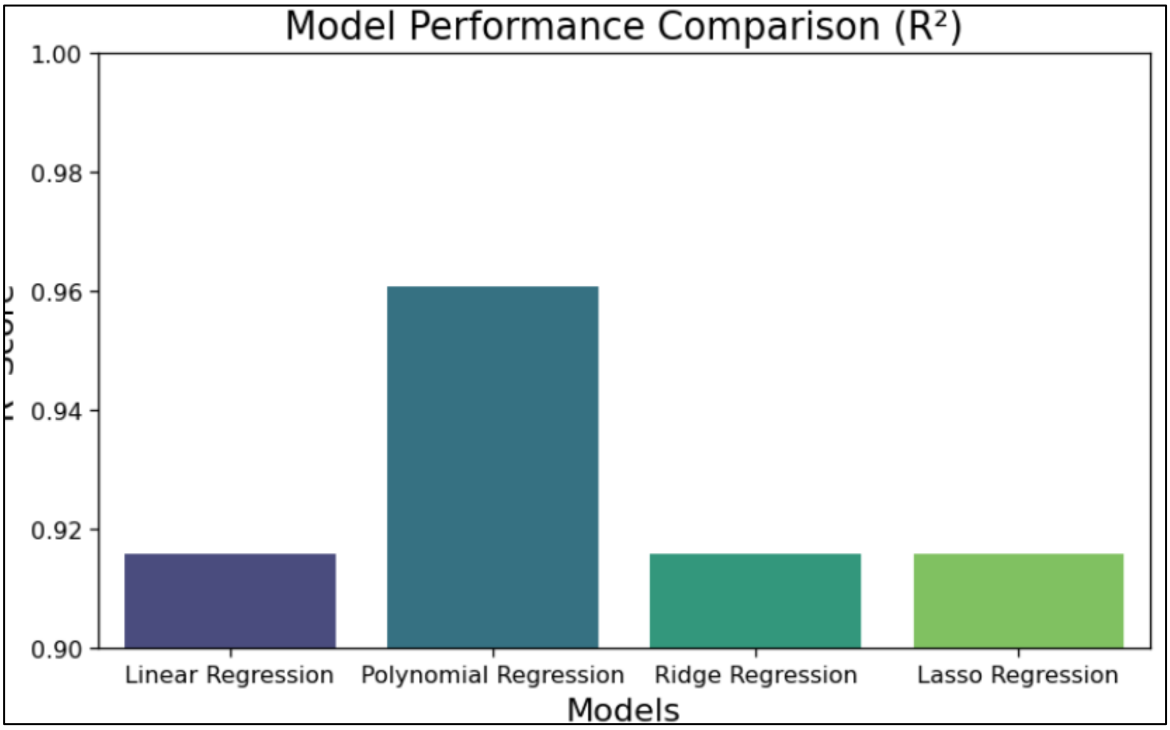

Figure 9. R^2 Bar Chart (R-squared values comparison for models)

Polynomial Regression achieves the highest R^2 value of **0.9609**, meaning it explains approximately **96.09%** of the variance in diamond prices. This demonstrates that it is highly effective for this dataset. All models have R^2 values above **0.90**, indicating that they explain a substantial portion of the variance in diamond prices. However, **Linear Regression** and **Ridge Regression** show the lowest R^2 values (**0.9158** and **0.9159**, respectively), which suggests they are less effective than Polynomial Regression. **Lasso Regression** achieves an R^2 of **0.9160**, slightly better than Linear and Ridge Regression, indicating that it captures some additional variance but still does not match the performance of Polynomial Regression. The high R^2 values across all models indicate that they all have a reasonable fit to the data, but the differences highlight the superiority of the **Polynomial Regression model** in this analysis. The relatively lower R^2 values for

Linear and Ridge Regression suggest that these models might benefit from incorporating more complex relationships or interactions between variables to improve their predictive accuracy.

Polynomial Regression consistently outperforms the other models in both metrics (MSE and R^2), suggesting it is the best choice for this dataset. **Linear and Ridge Regression** models may be too simplistic for the underlying complexity in the data, as indicated by their higher MSE values and lower R^2 scores. The **Lasso Regression** provides a slight improvement over Linear and Ridge, but still lags Polynomial Regression.

4. Discussion

The paper highlights that polynomial regression, with an R^2 of 0.9609, is most effective in capturing the complex relationships within the dataset. This result suggests that non-linear models provide substantial benefits in improving decision-making, particularly in fields such as pricing strategies, demand forecasting, and customer segmentation.

The results demonstrate that **Polynomial Regression** outperforms other models in capturing the complexities of the dataset. Regularized models such as Ridge and Lasso did not show significant improvement over Linear Regression but were helpful in avoiding overfitting. However, the high R^2 value of the polynomial model suggests that it captures a larger portion of the variance in the diamond pricing.

While polynomial regression improves accuracy, it also increases the model's complexity and could lead to overfitting on larger datasets. The model's interpretability decreases as the degree of polynomial increases, which could be problematic for business decision-makers looking for clear insights.

As quoted earlier, we can take examples of Amazon's use of machine learning for optimizing its supply chain and inventory management *(Bose & Mahapatra, 2018)* and companies like JPMorgan which have leverage AI to enhance fraud detection and risk assessment, illustrating how these models can be applied to improve both operational efficiency and decision accuracy *(Marr, 2019)*.

Furthermore, drawing from recent studies on AI in decision-making, such as *Shrestha et al. (2019),* AI systems have the potential to not only increase speed and accuracy but also reduce biases inherent in human decision-making. For instance, AI-driven models allow managers to make more objective decisions by analyzing patterns and trends that might be missed by human judgment.

Conclusion:

This paper demonstrates that machine learning algorithms play a crucial role in enhancing managerial decision-making across various business functions. Models such as decision trees, random forests, logistic regression, and support vector machines have proven effective in areas like marketing, finance, and operations, offering significant improvements in prediction accuracy, operational efficiency, and overall decision-making quality.

The integration of AI and machine learning allows businesses to process large datasets and generate insights that were previously unattainable, thereby reducing human biases and improving the objectivity of decisions. Furthermore, machine learning's ability to automate and optimize decision processes significantly contributes to long-term business performance and competitive advantage.

However, several challenges, such as the need for skilled personnel, ensuring data quality, and the interpretability of machine learning models, must be addressed to fully realize the potential of these technologies. For businesses to successfully adopt machine learning, efforts should be made to improve model transparency and interpretability, especially in critical decision-making contexts. Moreover, ensuring high-quality data is essential for maximizing the effectiveness of machine learning algorithms.

Machine learning offers substantial benefits for improving the accuracy, efficiency, and fairness of managerial decision-making. Continued research and advancements in AI will further optimize business outcomes by addressing current challenges and enhancing the transparency of machine learning models.

This paper highlights the effectiveness of polynomial regression in capturing non-linear relationships in diamond pricing. Regularized models such as Ridge and Lasso helped prevent overfitting but did not significantly outperform the linear baseline. Future efforts should focus on more complex models and the inclusion of external data to further improve prediction accuracy.

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Finally, we wish to acknowledge our family and friends for their unwavering support and encouragement throughout this journey. Their patience and understanding allowed us to focus and complete this work.

Thank you all for your contributions.

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Dataset: Dataset is taken from https://www.kaggle.com/

6. Conference Alignment

The paper aligns with the submission standards of the CSITY 2024 Conference.

The paper adheres to the required structure by clearly defining the problem, methodology, and results, and it demonstrates real-world applications, as encouraged by the conference guidelines.