PREDICTING DIAMOND PRICES WITH ANN USING DEEPLEARNING

A UG PROGECT PHASE -1 REPORT

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Submitted By

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CERTIFICATE OF COMPLETION

UG PROJECT PHASE -I

This is to certify that the **UG PROJECT PHASE -I** report entitled **" PREDICTING DIAMOND PRICES WITH ANN USING DEEP LEARNING"** is being submitted by **MD ABDUL JABBAR HUSSAIN (21UK1A05A8),** in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science & Engineering to Jawaharlal Nehru Technological University Hyderabad during the academic year 2024-2025, is a record of work carried out by them under the guidance and supervision.

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EXTERNAL

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ABSTRACT

Predicting diamond prices accurately is essential for the gem and jewelry industry, where pricing depends on various factors such as carat weight, cut, colour, clarity, and physical proportions. This study explores the use of Artificial Neural Networks (ANNs) powered by deep learning to develop a robust model for diamond price prediction. By utilizing a structured dataset, the model is trained to understand complex, non-linear relationships among the diamond attributes and their impact on pricing. Advanced preprocessing techniques, including normalization and feature selection, enhance model performance. The ANN architecture is optimized through hyperparameter tuning, employing multiple hidden layers and activation functions to improve prediction accuracy. The results demonstrate that the deep learning approach significantly outperforms traditional methods, providing reliable and precise price estimates. This research showcases the effectiveness of ANNs in addressing pricing challenges and offers a scalable, data-driven solution for stakeholders, contributing to more informed decision-making in the diamond market.

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1. INTRODUCTION

1.1 OVERVIEW

The task of predicting diamond prices involves estimating the value of a diamond based on key characteristics, such as carat weight, cut quality, colour grade, clarity, and physical proportions like depth and table size. Traditional pricing methods often rely on regression models or expert evaluations, which may not fully capture the complex, non-linear relationships between these attributes and their influence on pricing.

Artificial Neural Networks (ANNs), enhanced with deep learning techniques, provide a powerful alternative by leveraging their ability to model intricate patterns within data. In this approach, a dataset of diamond features and corresponding prices is used to train an ANN model. Preprocessing steps, such as feature selection, normalization, and outlier handling, ensure data quality and improve learning efficiency.

The deep learning framework involves designing an ANN architecture with multiple layers, activation functions, and optimized hyperparameters to enhance predictive accuracy. Techniques like backpropagation, dropout regularization, and adaptive learning rate optimization further refine the model's performance.

This method has shown promising results, significantly outperforming traditional regression approaches by delivering more precise and consistent price predictions. The application of deep learning in diamond price prediction not only automates and scales the process but also provides valuable insights into the key factors influencing diamond valuation, benefiting stakeholders across the gem and jewelry industry.

1.2 PURPOSE

The purpose of predicting diamond prices using Artificial Neural Networks (ANNs) and deep learning is to develop a precise, efficient, and scalable method for valuing diamonds based on their intrinsic attributes. This approach addresses several key objectives:

- **Enhance Pricing Accuracy:** By leveraging deep learning, complex, non-linear relationships between diamond features (e.g., carat, cut, colour, clarity) and prices can be captured, resulting in highly accurate price predictions.
- **Automate the Valuation Process:** Deep learning models provide an automated solution, reducing reliance on manual assessments and minimizing human errors, thereby streamlining the pricing process.
- **Provide Scalability and Consistency:** Unlike traditional methods that may vary across appraisers or regions, ANN models ensure consistent valuations regardless of scale or market conditions.
- **Uncover Key Influencing Factors:** The use of advanced algorithms allows for a deeper understanding of how different diamond characteristics influence price, offering insights that can inform marketing, design, and sales strategies.
- **Support Data-Driven Decision-Making:** Stakeholders, including jewelers, appraisers, and customers, can make informed decisions based on reliable, predictive analytics, fostering transparency and trust in the diamond market.
- **Adapt to Market Trends:** The flexibility of deep learning models enables them to adapt to evolving market trends and pricing dynamics, ensuring continued relevance in changing economic conditions.

By achieving these goals, ANN-based deep learning models transform the traditional diamond valuation process into a sophisticated, data-driven system that benefits the entire gem and jewelry industry.

2. PROBLEM STATEMENT

The accurate prediction of diamond prices is a challenging task due to the intricate interplay of various factors such as carat weight, cut quality, colour, clarity, and physical proportions like depth and table dimensions. Traditional pricing methods rely on regression models or manual evaluations, which are often limited by their inability to capture non-linear relationships and complex patterns within the data. These methods may result in inconsistent and suboptimal pricing, impacting both consumer trust and business profitability.

With the rise of large datasets and advancements in machine learning, there is an opportunity to leverage Artificial Neural Networks (ANNs) with deep learning to address these limitations. The problem lies in designing and implementing a robust predictive model capable of learning from diverse attributes to deliver accurate and reliable diamond price estimates. This involves overcoming challenges such as data preprocessing, feature selection, overfitting, and hyperparameter tuning.

The core objective is to develop an automated, scalable, and data-driven solution for predicting diamond prices, enabling stakeholders in the gem and jewelry industry to make more informed, objective, and efficient pricing decisions while uncovering the underlying factors that influence valuation.

3. LITERATURE SURVEY

3.1 EXISTING SYSTEM

In the current landscape of diamond price prediction, traditional methods dominate. These systems often rely on manual evaluations or simple statistical models, such as linear or polynomial regression. While these approaches provide a baseline for pricing, they are limited in their ability to handle the complexity and non-linear relationships inherent in diamond valuation.

Limitations of Traditional Systems:

1. Simplistic Models: Traditional regression models assume linear relationships between diamond attributes and prices, which fail to capture the nuanced interdependencies among factors like carat, cut, colour, and clarity.
2. Subjective Pricing: Manual pricing by experts is prone to human error and subjectivity, leading to inconsistencies in valuation.
3. Limited Scalability: Manual and traditional statistical methods are timeconsuming and not scalable for large inventories or real-time pricing.
4. Lack of Data Utilization: Traditional systems often underutilize available data, relying on pre-defined rules rather than learning patterns directly from the data.

Emerging Efforts with Machine Learning:

Recent advancements in machine learning have introduced predictive models using algorithms such as decision trees, support vector machines (SVMs), and ensemble methods like random forests. While these methods perform better than traditional systems, they still fall short in handling highly complex and multi-dimensional datasets. Artificial Neural Networks (ANNs), particularly those leveraging deep learning techniques, are beginning to emerge as a more powerful solution. However, the adoption of ANNs is still limited, with challenges such as selecting the optimal architecture, tuning hyperparameters, and managing computational costs.
The existing systems, while foundational, highlight the need for more sophisticated and automated solutions that can leverage deep learning to accurately predict diamond prices and address the inefficiencies of traditional methods.

3.2 PROPOSED SYSTEM

1. System Architecture

The system consists of the following components: I.

Data Layer:

○ A database or data source containing diamond attributes (e.g., CSV file, SQL database). ○ Attributes include:

- **Numerical Features**: Carat, Depth, Table, Dimensions (Length, Width, Height).
- **Categorical Features**: Cut, Colour, Clarity.
- **Target**: Price.

II. **Preprocessing Layer**:

○ Data cleaning and transformation pipeline:

- Handle missing data.
- Remove outliers.
- Normalize numerical features.
- Encode categorical features.

III. **Prediction Engine**:

○ Machine learning models for regression tasks:

- Random Forest, Gradient Boosting (e.g., XGBoost, LightGBM), or Neural Networks.

○ Feature selection and engineering pipeline. ○ Hyperparameter tuning using tools like Grid Search or Bayesian Optimization.

IV. **API Layer**:

- RESTful API to accept user input (diamond attributes) and return predictions.
- Frameworks: Flask.

V. **Frontend Interface**:

- A user-friendly interface (e.g., a web application or mobile app).
- Users input diamond attributes and receive price predictions.

VI. **Deployment and Monitoring**:

- Deploy the system on cloud platforms (e.g., AWS, GCP, Azure). o Monitor

performance using tools like Prometheus or New Relic. o

Regularly update the model with new data to ensure accuracy.

2. Workflow

I. **Data Input**:

- Users provide diamond attributes (Carat, Cut, Color, Clarity, Depth, etc.).

II. **Preprocessing**:

- Input data is preprocessed in real-time:
  - Missing values imputed.
  - Numerical features scaled.
  - Categorical features encoded.

III. **Prediction**:

- The preprocessed data is fed into the trained machine learning model.
- The model predicts the diamond price.

IV. **Output**:

- The predicted price is displayed to the user in the frontend interface or returned via the API.

3. Key Features

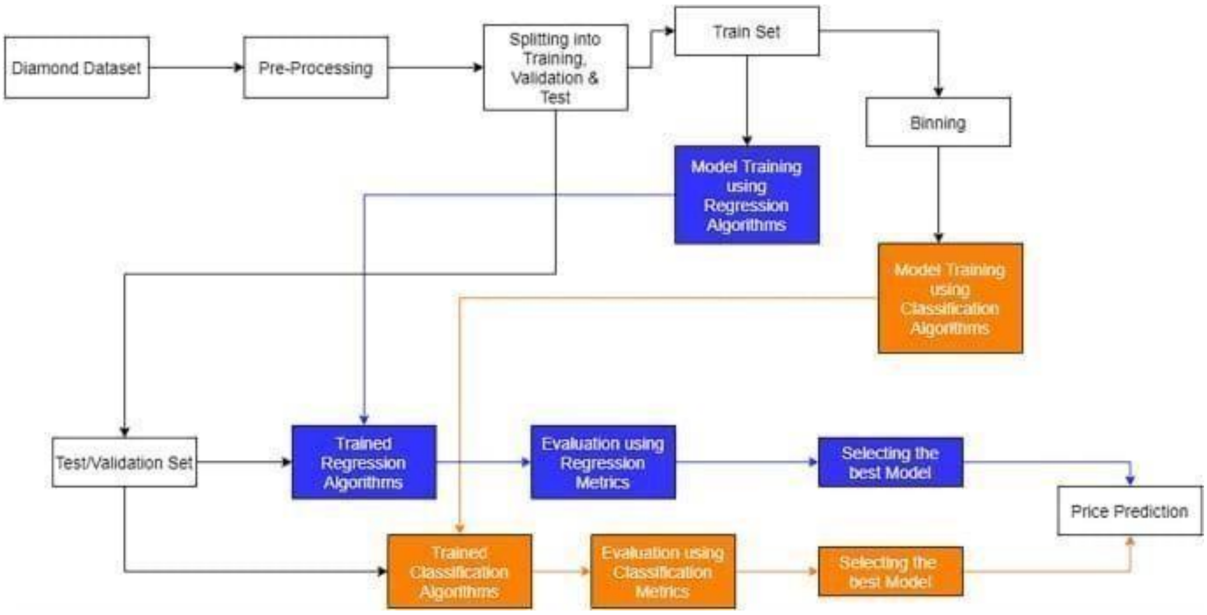
- **Scalable**: Can handle large datasets with millions of records.
- **Accurate**: Incorporates advanced machine learning models for high prediction accuracy.
- **User-Friendly**: Provides a clean and intuitive interface.
- **Adaptable**: Allows retraining with updated data.

4. Monitoring and Maintenance

- **Performance Metrics**:
  - Evaluate model predictions using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score.
- **Feedback Loop**: o Collect user feedback to improve predictions.
- **Model Updates**:
  - Periodically retrain the model using new data.

4. THEORITICAL ANALYSIS

4.1 BLOCK DIAGRAM



The diagram describes a diamond price prediction system using both regression and classification approaches.

1. **Diamond Dataset:** The input dataset containing diamond attributes and prices.

2. **Pre-Processing:** Cleaning and transforming the data (e.g., handling missing values, encoding features).

3. **Data Splitting:** Dividing the dataset into training, validation, and test sets for model training and evaluation.

4. **Model Training:**

   - Regression Algorithms: Predict the exact price using regression models. ○ Classification Algorithms (with Binning): Prices are grouped into bins, and classification models predict the bin.

5. **Evaluation:**

   - Regression models are evaluated using regression metrics (e.g., MAE, R^2).

- Classification models are evaluated using classification metrics (e.g., accuracy, F1-score).

6. **Model Selection:** The best-performing model from regression or classification is selected.

7. **Price Prediction:** The selected model predicts the diamond price.

4.2. HARDWARE/SOFTWARE DESIGNING

Category	Component	Short Description
Hardware Design	**Processor**	Multi-core processors (Intel i5/i7, AMD Ryzen 5/7) for efficient computations.
	RAM	8 GB minimum; 16 GB or more recommended for handling large datasets and models.
	Storage	SSD (256 GB or more) for fast data access and storage.
	GPU (Optional)	NVIDIA GPUs (e.g., RTX 3050, Tesla T4) for training complex models or deep learning tasks.
	Cloud Infrastructure	Use AWS, Google Cloud, or Azure for scalable model training and deployment.

Category	Tool/Framework	Short Description
Programming Language	Python	Widely used language for data preprocessing, modeling, and deployment.
Data Preprocessing	Pandas, NumPy	Libraries for cleaning, transforming, and analyzing diamond datasets.
Visualization	Matplotlib, Seaborn	Tools for creating visual insights (e.g., price trends vs attributes).
Machine Learning	Scikit-learn, XGBoost, LightGBM	Libraries for building regression or classification models for price prediction.
Deep Learning	TensorFlow, PyTorch	Frameworks for implementing advanced neural networks (if necessary).
Model Tuning	GridSearchCV, Optuna	Tools for optimizing model hyperparameters.
Backend Framework	Flask, FastAPI	Frameworks for deploying the model as an API.
Frontend Framework	React, Angular	For building user interfaces to input data and display predictions.

5. EXPERIMENTAL INVESTIGATION

An experimental investigation into predicting diamond prices involves creating a model that estimates the value of diamonds based on various features. These features include **carat**, **cut**, **colour**, **clarity**, **shape**, and **certification**. The steps in the investigation are as follows:

1. **Data Collection**: Gather data from online retailers, auctions, and specialized databases.

2. **Data Preprocessing**: Clean the data, handle missing values, and encode categorical variables.

3. **Exploratory Data Analysis (EDA)**: Analyze correlations and visualize trends in diamond prices.

4. **Model Selection**: Choose predictive models such as Linear Regression, Decision Trees, or Gradient Boosting.

5. **Model Evaluation**: Split data into training and testing sets, use cross-validation, and assess performance with metrics like MAE, RMSE, and R^2.

6. **Model Tuning**: Optimize hyperparameters and create new features to improve predictions.

7. **Prediction and Sensitivity Analysis**: Predict diamond prices and analyze how changes in features affect prices.

8. **Interpretability**: Use techniques like feature importance or SHAP values to explain the model's predictions.

ALGORITHM USED

When using an Artificial Neural Network (ANN) to predict diamond prices, the algorithm typically follows these steps:

1. Data Preparation

- **Feature Selection:** Collect relevant features about diamonds (e.g., carat, cut, color, clarity, table, depth, price, etc.).
- **Data Cleaning:** Handle missing values, outliers, or incorrect entries in the dataset.
- **Normalization/Standardization:** Scale the features (e.g., carat weight and table percentages) to ensure that the ANN handles them effectively. Neural networks work better when input values are normalized to a range like [0, 1] or standardized to have zero mean and unit variance.
- **One-Hot Encoding:** Convert categorical features (e.g., cut, colour, and clarity) into numerical format using techniques like one-hot encoding.

2. Designing the Neural Network

- **Input Layer:** The number of neurons corresponds to the number of input features (e.g., carat, cut, color, etc.).
- **Hidden Layers:** Add one or more hidden layers with an appropriate number of neurons. Common choices are 1–3 layers with 64–128 neurons in each layer for regression problems like this.
- **Activation Functions:**
  - Use activation functions like **ReLU (Rectified Linear Unit)** in hidden layers for non-linearity.
  - For the output layer in price prediction, no activation (linear activation) is commonly used since it’s a regression problem.

- **Output Layer:** One neuron is used for the predicted price.

3. Training the ANN

- **Loss Function:** Use **Mean Squared Error (MSE)** or **Mean Absolute Error (MAE)** as the loss function since this is a regression task.
- **Optimizer:** Use optimizers like **Adam** or **Stochastic Gradient Descent (SGD)** for adjusting weights.
- **Epochs and Batch Size:**
  - Train the network over multiple epochs (e.g., 50–200).
  - Use mini-batches for faster and more stable training.
- **Training-Validation Split:** Split the data into training and validation sets to monitor model performance during training.

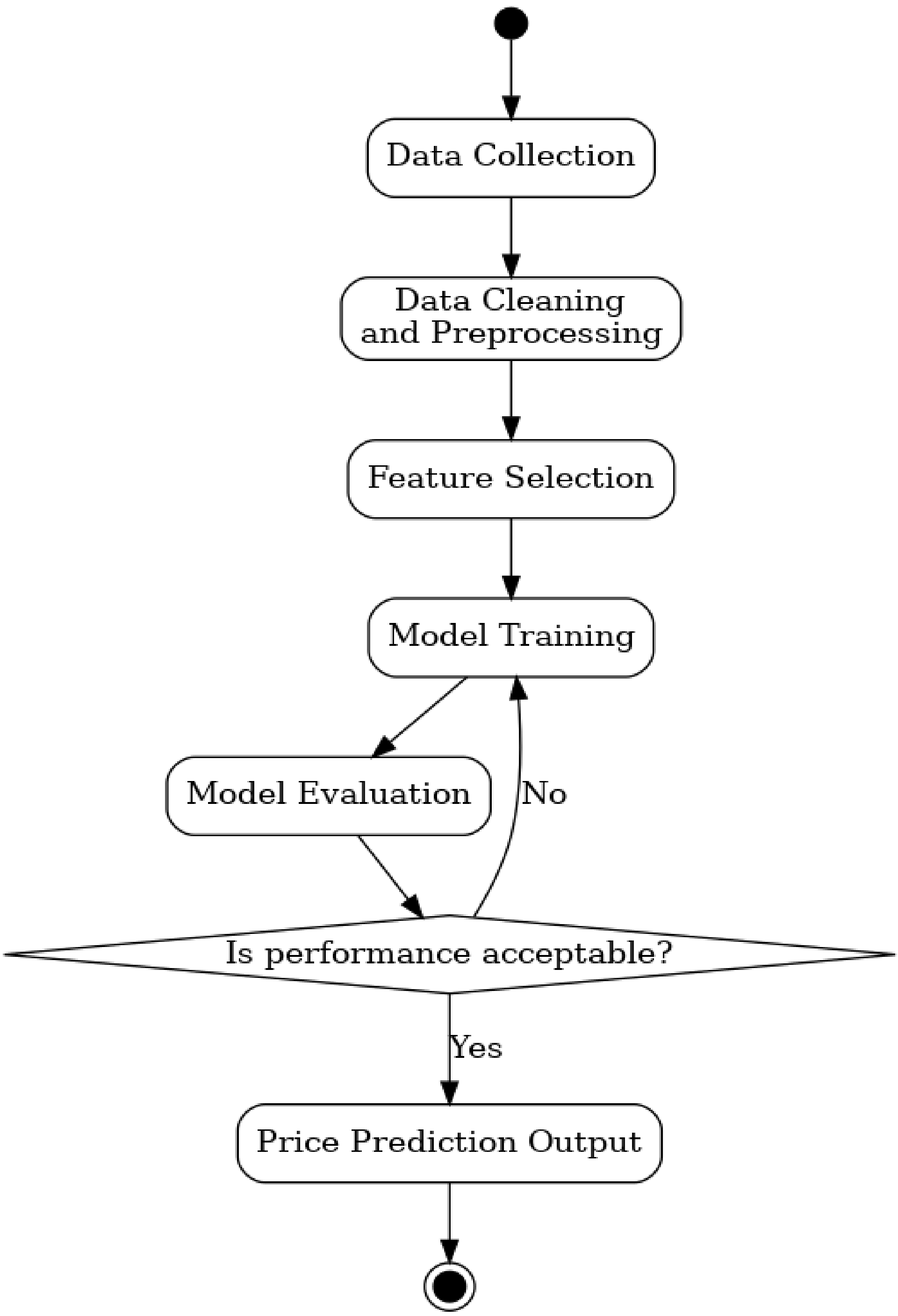
4. Evaluation

- Evaluate the ANN on a **test set** using metrics like:
  - **MAE (Mean Absolute Error)**
  - **MSE (Mean Squared Error)**
  - **RMSE (Root Mean Squared Error)**
- Compare predictions against the true prices to assess model accuracy.

5. Deployment

- Once trained, the ANN model can predict the price of diamonds for new data inputs.

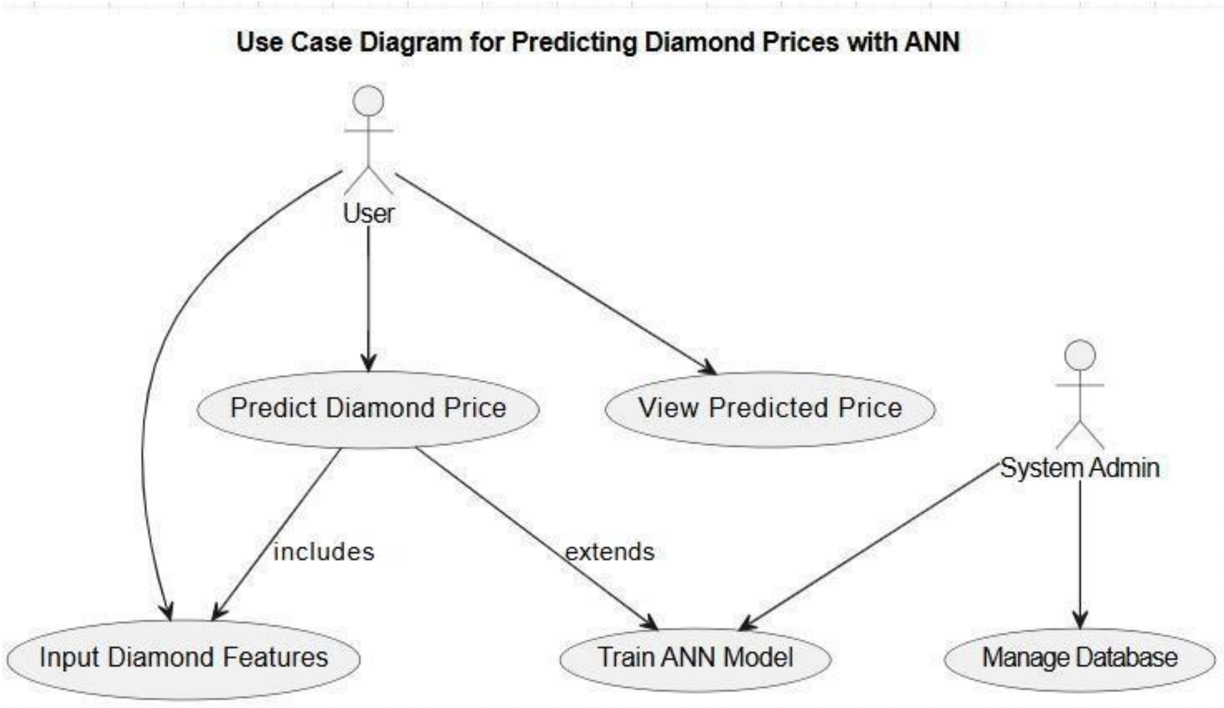
6. FLOWCHART



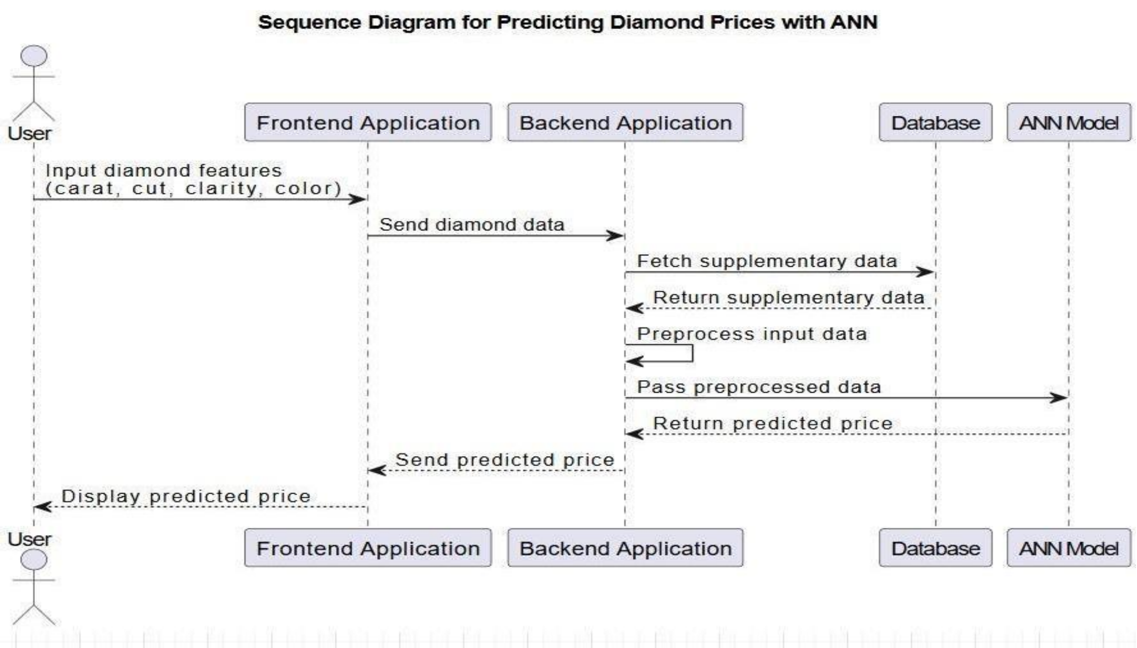
Data Collection
Data Cleaning and Preprocessing
Feature Selection
Model Training
Model Evaluation
No
Is performance acceptable?
Yes
Price Prediction Output

7. UML DIAGRAMS

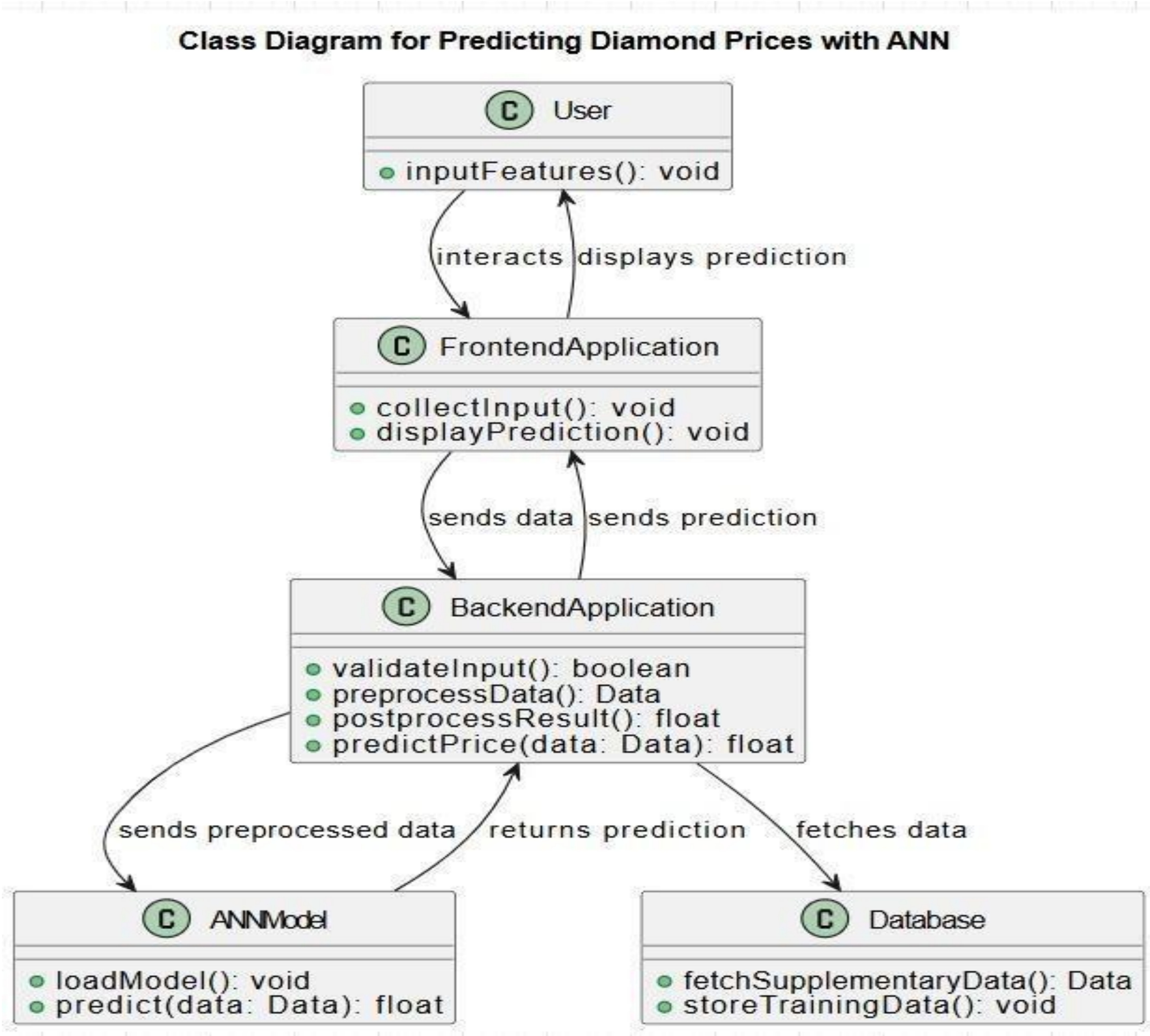
1. USE CASE DIAGRAM



2. SEQUENCE DIAGARAM



3. CLASS DIAGRAM



8. CONCLUSION

predicting diamond prices involves understanding and modeling the complex relationship between various intrinsic and extrinsic factors that determine the value of a diamond. Key attributes such as carat weight, cut quality, colour, clarity, and shape all contribute to the overall price of a diamond. Additionally, market conditions, location, and certification from reputable grading organizations like the GIA also play a significant role in shaping pricing trends.

The theoretical approach to predicting diamond prices is grounded in the assumption that these features can be quantified and analyzed using statistical and machine learning techniques to uncover patterns that can predict pricing with a reasonable degree of accuracy. By leveraging historical data and sophisticated models like linear regression, decision trees, random forests, and gradient boosting algorithms, one can capture both linear and non-linear relationships between features and prices.

Furthermore, the theoretical framework assumes that market behavior is driven by observable factors like consumer demand, supply dynamics, and industry standards, but it also acknowledges the challenges presented by unseen variables such as economic shifts or changes in consumer preferences, which may not always be directly reflected in the available data.

The key challenge in predicting diamond prices is not just modeling the relationships between the known features, but also ensuring that the model can generalize well to unseen diamonds or changing market conditions. Therefore, models need to be regularly updated and tested to maintain their relevance over time.

In conclusion, predicting diamond prices in theory hinges on a clear understanding of the variables influencing diamond value and the application of appropriate analytical techniques. Although no model can account for all variables, a well-constructed predictive model can serve as a powerful tool for stakeholders in the diamond market, offering valuable insights for pricing strategies, investment decisions, and consumer choices. The theory behind diamond price prediction offers the potential for enhancing transparency, improving market efficiency, and enabling better decision-making in the diamond industry.

9. FUTURE SCOPE

The future scope for predicting diamond prices is expansive and could be transformed by innovations in machine learning, real-time data integration, blockchain transparency, and the incorporation of consumer behaviour and sentiment analysis. As technology evolves, diamond price prediction models will become more personalized, accurate, and adaptive, providing valuable insights to stakeholders across the diamond industry from retailers and investors to consumers and graders. The ability to predict not just the current price but also future market trends and consumer preferences will be crucial in maintaining competitiveness and making informed decisions in an ever-changing market.

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