International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 10, pp 406-416, October-2023

https://doi.org/10.47001/IRJIET/2023.710054

"Gemo": An AI-Powered Approach to Color, Clarity, Cut Prediction, and Valuation for Gemstones

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***Abstract* - "Gemo" is an AI-powered smartphone application that aims to improve the gem industry by replacing human-based approaches with computer-based ones. A mix of well-trained machine learning models that are capable of color identification, cut projection, recommendation, and pricing prediction is competent in offering experience and information to the industry. Traditional gem industry predictions are often subjective and inaccurate due to reliance on human labor. Erroneous output caused financial loss. Gemo is developed to overcome these problems by applying Artificial intelligence-based feature identification of gemstones and leads to expect more accurate and real-time results. Integration of Machine learning, Artificial Intelligence, and Natural Language Processing based technology, boosted the realism of the gem analysis process. "Gemo" is applied via advanced machine learning-based algorithms that capture the features of color, clarity shape, and intrinsic attributes of gemstones. Color detection model extraction of the Hue, Saturation, and Value (HSV) colors from gemstone pictures, delivering a cutting-edge and accurate approach to color recognition. The cut prediction approach lowers subjectivity and inaccuracy during the prediction of the cut by employing 3D image processing methods. The recommendation model gathers human preferences and forecasts the optimum solution using Natural Language Processing (NLP). Lastly, the valuation model utilizes the 4Cs features to provide a pricing range for the gemstones, resulting in a complete and advanced gemstone analysis system. The "Gemo" model, which integrates multiple ML-based models, increases the criteria for the gemstone sector. This will help gem experts excel and increase industry competitiveness.**

Keywords: Gemstone, Gemstone Cut, Clarity, Color, Price, Prediction, Identification.

I. INTRODUCTION

Gemstones are rare and beautiful minerals found in different countries due to geographical location, geological composition, and mining practices. These precious stones are valuable resources used to create luxury items like jewelry, watches, and home decor [1]. Exporting these gemstones provides countries with a significant source of foreign exchange. Asian countries, such as India, Sri Lanka, Madagascar, Australia, and Brazil, are major sources of gemstones, and they are in high demand from European countries like the United States and France, driving the gemstone market [2].

Production stages of the gem industry can be categorized into four main stages: Mining and identification of gemstones, feature detection of gemstones, gem cutting, pricing, and marketing of gemstones. Most of the countries in the world are currently doing these processes with many human interactions [3]. As a reason for that, a significant number of professions have grown around this industry. Gem mining [4] requires geologists and other specialists to study the land and its geological formations to identify potential gem-bearing areas. Then digging, sorting, washing, and extracting processes require much labor [5]. The extraction of these gemstones requires expertise and knowledge in identification, feature detection, cutting, and valuation processes. The evolution of the high number of human laborers caused them to spend large amounts of money on labor costs [6]. As well as human bias and human errors can affect the accuracy of industrial processes.

Categorizing these gemstones into multiple classes requires a proper analysis of 4c characteristics color, clarity, cut, and carat weight [7]. Analysis of these characteristics using human inspection can be affected by human bias. To reduce this human labor and human bias that occurs during human inspection, the most suitable method is avoiding traditional human-based approaches and applying modern

ISSN (online): 2581-3048
Volume 7, Issue 10, pp 406-416, October-2023
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computer-based approaches such as machine learning, computer vision, deep learning, etc. This research focuses on reducing human labor costs by developing Machine learning (ML), Computer vision (CV), and a Natural Language Processing (NLP) based mobile application called “Gemo”

“Gemo” is an AI-based gem advisor that is capable of identifying gemstones, cut predictions, price predictions, and recommendations based on well-trained machine learning models. It aims to revolutionize the gem industry by avoiding the industry from traditional human-based approaches and replacing them with cost-effective and more reliable modern computer-based approaches.

The color and clarity detection model of the application explores the use of image recognition models and image processing methods to determine gemstone color and clarity in the gem business. Traditionally, gemologists used spectroscopy to identify gemstone spectra and absorbed wavelengths [8]. Image processing allows for the extraction of Hue, Saturation, and Value (HSV) colors from gemstone photos, offering a cutting-edge and accurate method for color identification. Furthermore, image processing plays a vital role in assessing gemstone clarity by detecting and classifying inclusions and flaws in high-quality digital images, providing a more precise and objective examination compared to traditional methods.

Cut prediction based on human expertise can be subjective and vary from one individual to another. Different gem cutters may have different interpretations and preferences, leading to variations in the recommended cuts [9]. This subjectivity can result in inconsistencies in the final cut quality and hinder standardization within the industry. To overcome these challenges and enhance cut prediction in the gemstone cutting industry, the integration of AI and 3D computer vision technology is proposed. Gemo, the innovative mobile application, deals with 3D computer vision to capture detailed gemstone information, eliminating subjective interpretations and providing objective data for analysis. The AI-driven cut prediction model analyzes gemstone characteristics and provides insights based on industry standards and best practices, enhancing accuracy and consistency.

The process of gemstone identification and recommendation in the local market has been traditionally reliant on the expertise of gemstone experts and jewelers. This conventional approach can be subjective and may lead to variations in gemstone suggestions, not always aligning with the individual preferences and requirements of customers [10]. Moreover, the limited availability of expert opinions and the time-consuming nature of personalized consultations can hinder the overall buying experience for consumers. To address these challenges and revolutionize the gemstone market experience in Sri Lanka, advancements in Natural Language Processing (NLP) have garnered significant attention. NLP techniques have shown promising applications in various domains, such as sentiment analysis, text summarization, and machine translation. However, the specific utilization of NLP for personalized gemstone identification and recommendation remains largely unexplored.

Accurately estimating the value of gemstones in the rapidly evolving gemstone industry [11] is another challenging task that frequently requires the expertise of qualified evaluators. Traditional evaluations consider several variables, including the purchase date, gemstone name, color, clarity, carat weight, and cut. While the industry has historically benefited from these techniques, recent developments in data analytics and machine learning offer an excellent argument for a more accurate and effective valuation procedure. This research approach provides valuable insights into the gemstone market, supporting investment decisions and pricing strategies. Empirical evidence and experimental results reinforce the efficiency of these modern approaches in enhancing gemstone price forecasting, showcasing their potential applicability in real world scenarios.

The creation of the AI-powered mobile application marks a significant leap forward in the human-based processes of the gem industry. "Gemo" redefines gemstone color, clarity, and cut predictions by utilizing the power of image recognition, image processing, and 3D computer vision, offering a more accurate, objective, and standardized method. Additionally, the use of NLP approaches improves the experience of purchasing gemstones by enabling individualized identification and recommendations that match buyer expectations with industry knowledge. The research presented here highlights the potential of data analytics and machine learning in changing gemstone valuation by providing accurate and efficient price predictions to assist in educated investment decisions. By replacing the traditional human-based approach with a modern computer-based approach, Gem Business is prepared to increase efficiency, reduce expenses, and human interaction to establish a more dynamic and prosperous future.

II. BACKGROUND STUDY

The gemstone industry has a rich history, representing cultural heritage and aesthetics [12]. In recent times, it has experienced significant technological advancements and data-driven approaches. Gemstones have long been treasured for their unique beauty, rarity, and symbolic significance. From

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engagement rings to decorative jewelry pieces, gemstones play a prominent role in various cultural and personal contexts. However, the process of identifying and selecting the right gemstone that aligns with individual preferences and requirements can be challenging and subjective [13].

Overall, the integration of AI, 3D computer vision, gemstone evaluations considering its characteristics, detection of the colors of gemstones, and NLP technologies promises to revolutionize the gemstone industry, offering standardized and data-driven approaches. The research objectives include improving precision, efficiency, and transparency in gemstone processes, benefiting the industry and stakeholders.

2.1 Gemstone Cut Prediction

Gem cut prediction and automation play a major role in the gem-cutting process, where the value and beauty of gemstones depend heavily on the precision and quality of their cuts. While traditional human-based approaches have been widely used, there are significant challenges such as subjectivity, variations in interpretations, and limitations in expertise [14]. These factors can result in inconsistencies, biases, and errors in cut recommendations. Additionally, the lack of standardized guidelines and documentation usage affected the evaluation and comparison of cut quality across different gemstones and gem cutters. However, the innovation of advanced technologies, including AI and 3D computer vision, offers a promising solution to address these challenges. Through the application of computer vision algorithms, image processing methods, and machine learning models, significant developments have been made in the analysis of gemstone features, the development of detailed 3D models, and the prediction of appropriate cuts in recent years [15]. These developments have the capability to completely change how gem cuts are predicted, improving accuracy, efficiency, and industry standardization. However, despite these significant advancements, it is crucial to point out that there is still a lack of complete research in this field.

2.2 Color and Clarity Identification

The referenced work proposes a machine-learning technique for automatic gemstone categorization and value estimation based on microscopic images captured using a gemological microscope. The method utilizes a Convolutional Neural Network (CNN) to identify the type of gemstone and considers various characteristics such as kind, color scheme, form, and weight to estimate its value. The approach was tested on four different gemstone types, achieving high accuracy rates of 87% for Yellow Sapphire and 77% for Blue Sapphire. The study emphasizes the importance of the original image's quality in accurately determining the gemstone's precise hue, with Yellow Sapphires having maximum contrast resulting in the most accurate color classification. Overall, the technique shows promising potential for automated gemstone categorization and value assessment.

2.3 Personalized gemstone recommendation

The traditional gemstone selection process relies heavily on expert knowledge, which introduces subjectivity and bias. This manual approach poses challenges for nonexperts, who often find the process complex and intimidating. Natural Language Processing (NLP) models have demonstrated their effectiveness in understanding user requirements across various domains. However, when it comes to gemology, their application has not been thoroughly explored. In the field of gemology, content-based recommendation systems are utilized to analyze the attributes of gemstones, enabling them to provide personalized suggestions. On the other hand, collaborative filtering techniques take into consideration both user preferences and the behavior of similar users to make recommendations. Despite their success in other areas, the potential of NLP models in gemology remains unexplored.

2.4 Price Prediction of Gemstones

The valuation of gemstones depends on multiple factors, including color, cut, carat weight, and clarity. Accurate price forecasting is crucial for stakeholders in the gemstone market. This background study examines statistical modeling, machine learning, and artificial intelligence techniques used to predict gemstone prices. By analyzing historical auction records, gemological reports, and market trends, researchers aim to establish transparent and efficient pricing mechanisms. A method is presented for the value estimation of gemstones using a gemstone dataset [16]. It highlights the potential of CNNs in extracting relevant features from gemstone images and accurately predicting gemstone values. However, the study does not incorporate all the key factors such as Color, Clarity, Carat Weight and Cut of the gemstone. Another approach is the application of neural networks in regression problems involving qualitative data, such as gemstone valuation [17]. It demonstrates the effectiveness of neural networks in predicting gemstone values based on subjective attributes. While this study does not explicitly consider the key factors mentioned, it highlights the potential of neural networks for accurately estimating gemstone values using qualitative data.

III. METHODOLOGY

The below Figure 1 diagram represents all four components of this system, and how each component utilized its functionality through the application.

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https://doi.org/10.47001/IRJIET/2023.710054

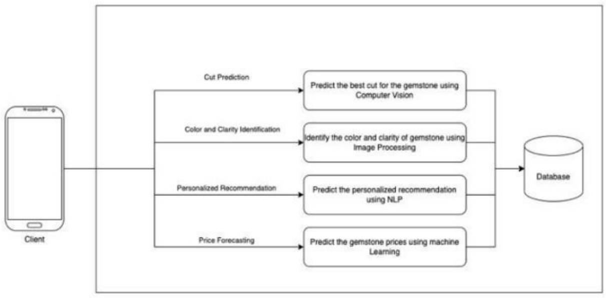

Figure 1: Overview of the system

3.1 Gemstone Cut Prediction

The methodologies employed in this research study for cut prediction involve four main approaches. Firstly, the gemstone features are analyzed, and a point cloud reconstruction is performed based on the acquired data. Secondly, the reconstructed point cloud detailed analysis to extract relevant information. Next, structural mapping techniques are applied to identify the best mapping structure to the point cloud. Finally, using the analyzed features and structural mapping results, an optimal cut is predicted. The below Figure 2 diagram represents all four approaches of this system, and how each component utilized its functionality through the mobile application.

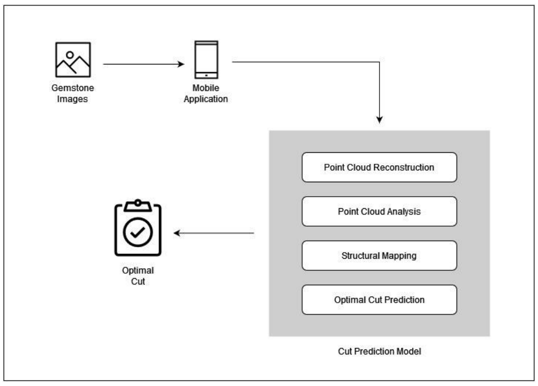

Figure 2: Component Diagram of Cut Prediction

This research encompassed three main phases: data acquisition, data preprocessing, and model training and evaluation. Data acquisition involved obtaining a dataset of 620 gemstone images, categorized into three classes (oval, square, and trilliant) with cut recommendations from experienced gem cutters. Mr. Gamini Gunaseela of Migoto Gems Pvt Ltd in Sri Lanka supervised this process.

In the data preprocessing phase, the images were aligned, registered, and cleaned to enhance their quality. Depth estimation algorithms were applied to create depth maps, enabling the generation of detailed 3D point clouds. The point clouds were further refined by removing outliers.

For model training and evaluation, TensorFlow, torch, and transformers libraries were used. A modified InceptionResNetV2 served as the feature extractor in the model architecture, which included global average pooling, dropout layers, and dense layers. Softmax activation generated class probabilities for cutting points, with categorical cross-entropy as the loss function. Training progress was monitored using metrics like accuracy, precision, recall, and AUC over 150 epochs. Confusion matrices aided in identifying misclassifications, ultimately providing a foundation for precise gemstone cut identification and enhancing decision-making processes.

3.2 Color and Clarity Identification

This study focuses on the development of a sophisticated system capable of recognizing gemstones from the Corundum, Topaz, and Chrysoberyl Families. It was also capable of precisely determining their color and clarity attributes, adding a layer of sophistication to gemstone classification.

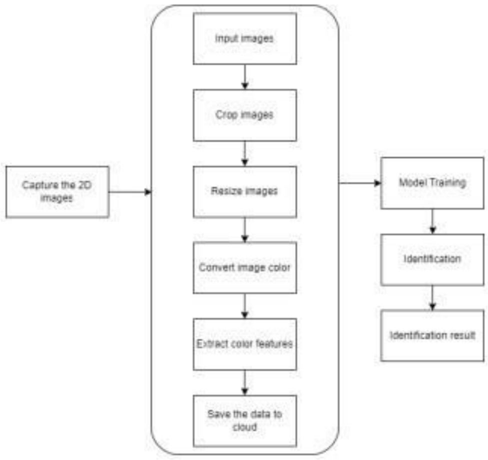

Figure 3: Component diagram of Color and Clarity Identification

The above Figure 3 represents the approach for color and clarity identification. The dataset used comprises over 700 images, segregated into three categories: variety, color, and clarity models. This partitioning facilitates specialized training for each model.

The study methodology, which is adapted to several CNN architectures such as Xception, ResNet50, and Inception ResNet V2, strongly emphasizes data preparation and augmentation. Model generalization is improved by real-time data augmentation techniques as rotation, shear, zoom, and horizontal flip. This thorough preprocessing optimizes the learning process for several gem properties by ensuring that input photos match architecture-specific constraints.

The system's model architecture, known as the "gem detector," leverages pre-trained CNN models with ImageNet

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weights for transfer learning. The architecture includes global average pooling, dropout, dense layers, and SoftMax output, optimizing classification while mitigating overfitting. The compilation phase configures the model with an Adam optimizer, a learning rate of 0.0001, and categorical cross entropy as the loss function. Evaluation metrics like categorical accuracy, precision, recall, and AUC are defined to gauge model performance. The following Figure 4 represent image processing workflow.

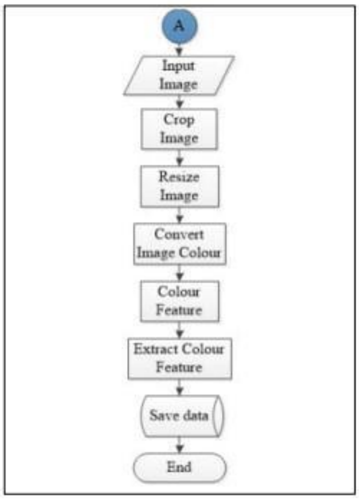

Figure 4: Image Processing Workflow

The represents process unfolds over 250 epochs, with training data provided through a data generator. Upon completion, the trained model is saved for future gemstone identification tasks. This methodology showcases a systematic approach to deep learning-based gemstone identification, offering practical applications across diverse fields.

3.3 Personalized gemstone recommendation

The development of the Gemstone Recommendation system, integrating both the GRU-based sequence model. For the GRU-based model a comprehensive CSV dataset with 2000 gemstone names along with corresponding textual descriptions collected from books and domain experts. The dataset underwent thorough preprocessing, including lowercase conversion for consistency, tokenization, removing numerical characters and punctuation, lemmatization for word normalization, and removing stopwords to guarantee the quality and relevancy of textual data. The following Figure 5 represents the component diagram of recommendation system.

Figure 4: Component Diagram of recommendation

To prevent bias during training, an analysis of the distribution of gemstone types in the dataset was conducted. The dataset was balanced using shuffle techniques. Additionally, histograms were used to determine the ideal maximum sequence length for the model input by visualizing the distribution of token lengths in the preprocessed text data.

The GRU model architecture was crafted using TensorFlow and Keras libraries, incorporating bidirectional layers for sequence modeling. Subnetworks featuring dense layers, batch normalization, and dropout mechanisms were integrated to extract features from gemstone descriptions. This RNN architecture aimed to capture key attributes, enabling accurate gemstone recommendations. The training process was carried out using a batch size of 64 and training for a maximum of 200 epochs. The following diagram represents workflow of recommendation system.

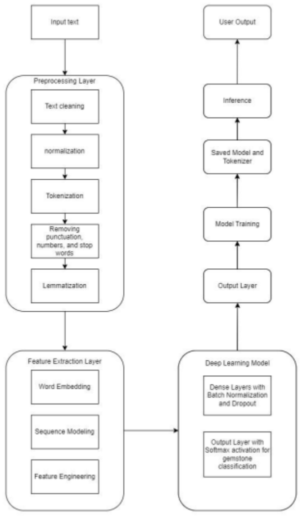

Figure 5: Approach for Recommendation

3.4 Price Prediction of Gemstones

This study's main objective is to analyze in detail seven different gemstones: sapphire, ruby, alexandrite, spinel, zircon, cat's eye, and topaz. To learn more about their market behavior and price trends, these priceless gemstones went through deep studies. The study includes a sizable dataset that was directly collected from Sri Lanka's local market, capturing important information on various factors that affect gemstone prices. The below Figure 7 represent the component diagram of price prediction.

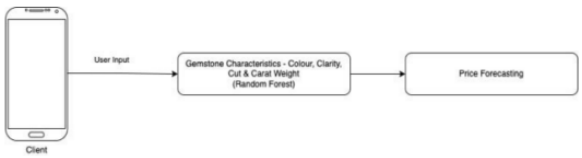

Figure 6: Recommendation model workflow

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The dataset carefully records important details like the date of sale, the specific gemstone's name, its unique color and clarity characteristics, the cut that enhances its brilliance, the carat weight that signifies its size, and most importantly, its corresponding price. This comprehensive dataset contains a significant amount of data, with between 650 - 700 rows of carefully collected data points.

An advanced regression approach was used to analyze the complex relationship between these attributes and the prices of the gemstones. Random Forest was a natural choice to forecast gemstone prices based on the combination of attributes because it is known for its effectiveness in capturing complex patterns and because it provides a thorough understanding of how various features together impact price variations.

To make accurate forecasts, the data went through careful pre-processing. The dataset had to be cleaned, transformed and made ready for analysis through a number of steps. Furthermore, the dataset was judiciously split into two segments to accurately assess the performance of the predictive model. The model was trained on 80% of the data to help it understand complex relationships and the remaining 20% was set aside for thorough evaluation that simulated real-world scenarios.

IV. RESULTS AND DISCUSSION

4.1 Gemstone Cut Prediction

The excellent overall accuracy of 72% achieved by the gemstone cut prediction model is remarkable. The model predicts the optimal cut to the gemstone correctly in 72% of cases, highlighting the program's accuracy in classifying it into optimal cuts.

	precision	recall	f1-score	support
oval	0.77	0.76	0.76	45
square	0.72	0.75	0.73	44
trilliant	0.65	0.63	0.64	35
accuracy			0.72	124
macro avg	0.71	0.71	0.71	124
weighted avg	0.72	0.72	0.72	124

Figure 8: Classification Report of cut prediction

The outcomes show the accuracy and usefulness of the gemstone cut prediction model. Its ability to achieve outstanding precision and recall values across numerous categories demonstrates its potential to automate the gemstone cut prediction process. The model's exceptional overall accuracy inspires confidence in its suitability for realworld uses in determining gemstone cutting. This has favorable repercussions for disciplines like gemological research and jewelry appraisal. The following Figure 9 represent results of confusion matrix.

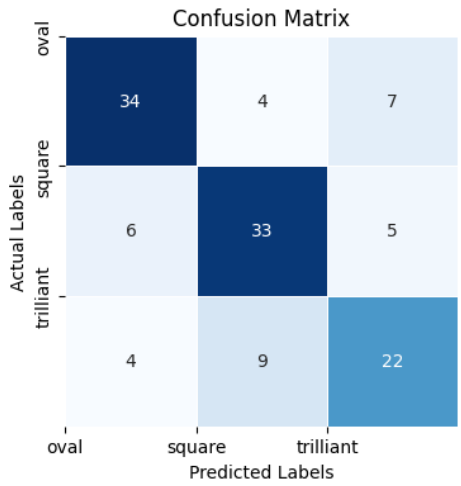

Figure 9: Cut Prediction Confusion Matrix

4.2 Color and Clarity Identification

The classification report that is currently being distributed details how well our approach for detecting gemstone kinds performs. Key metrics that measure the model's precision, recall, F1-score, and general accuracy are included in the report. The following Figure 10 represents classification report of variety model.

Found 722 images belonging to 4 classes.

========== Classification Report ==========

	precision	recall	f1-score	support
Alexandrite	0.99	0.96	0.97	206
Cats Eye	0.79	0.94	0.86	35
Sapphire	0.99	0.98	0.99	361
Topaz	0.94	0.98	0.96	120
accuracy			0.97	722
macro avg	0.93	0.97	0.95	722
weighted avg	0.97	0.97	0.97	722

Figure 10: Classification Report of variety model

The given results highlight the accuracy and reliability of the gemstone variety model. Its promise for automating gemstone variety classification is demonstrated by the high precision and recall values attained in a range of categories. The model's impressive overall accuracy gives confidence to its practical applicability in gemstone identification procedures, with positive implications for the gemological research and jewelry evaluation industries. The following Figure 11 represents confusion matrix of variety model.

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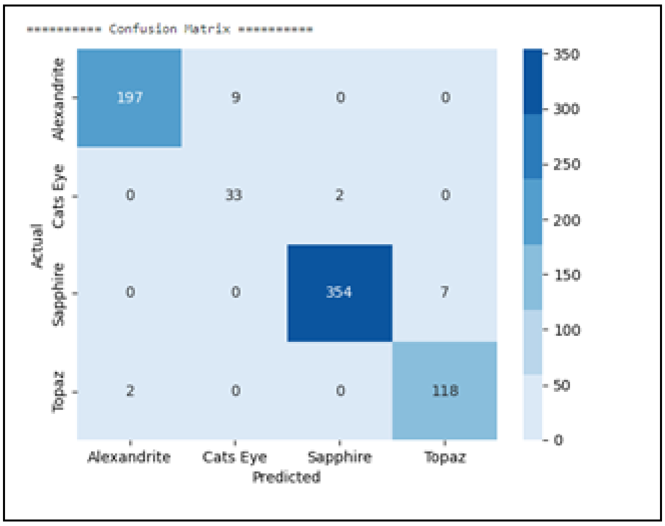

Figure 11: Confusion Matrix of variety model

The classification report on the performance of the gemstone color model is presented in the output that is given. This report provides a brief review of how well the model has done in classifying gemstones according to their hue. Here is a concise list of the main ideas.

========== Classification Report ==========

	precision	recall	f1-score	support
BLACK	0.94	0.91	0.92	33
BLUE	0.99	0.98	0.98	289
GREEN	0.70	1.00	0.82	14
PINK	1.00	0.96	0.98	71
PURPLE	0.96	0.96	0.96	69
RED	0.96	0.97	0.97	73
WHITE	0.94	0.97	0.96	33
YELLOW	0.99	0.99	0.99	140
accuracy			0.97	722
macro avg	0.93	0.97	0.95	722
weighted avg	0.97	0.97	0.97	722

Figure 12: Classification Report of color

In conclusion, the color model performs well, with a 97% accuracy rate. Its superior ability to accurately classify gemstone colors is demonstrated by its high precision and recall values for a variety of color categories. The balanced F1-scores highlight the model's dependable performance even further. These findings demonstrate the model's capability to automate gemstone color identification, which has important ramifications for sectors of the economy that depend on accurate gemstone color evaluation.

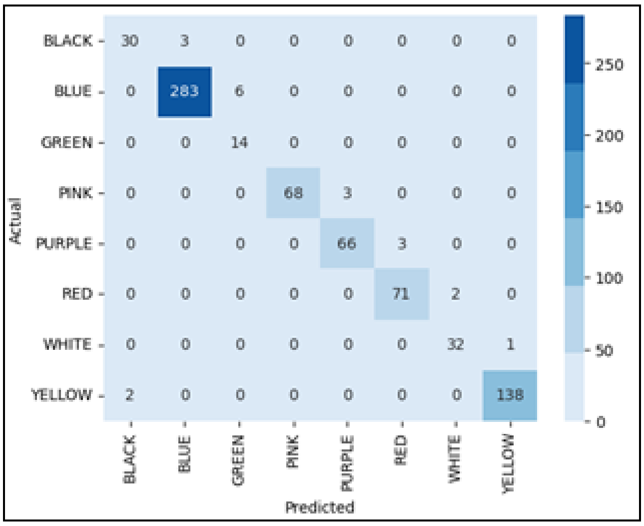

Figure 13: Confusion Matrix of Color

The clarity model's outstanding performance in accurately classifying gemstone clarity levels is highlighted in the classification report that was produced for it. Key metrics showing the model's precision, recall, and F1-score for several clarity categories are clearly presented in the report.

========== Classification Report ==========

	precision	recall	f1-score	support
I	0.98	0.97	0.98	182
SI	0.97	0.94	0.96	180
VS	0.95	0.99	0.97	182
VVS	0.99	0.98	0.99	178
accuracy			0.97	722
macro avg	0.97	0.97	0.97	722
weighted avg	0.97	0.97	0.97	722

Figure 14: Classification Report of clarity

In conclusion, the clarity model performs well and is 97% accurate. Its competence in precise gemstone clarity rating is supported by its high precision and recall values across various clarity levels. These results highlight the model's ability to automatically classify gemstone clarity, which has ramifications for companies that rely on accurate gemstone assessment.

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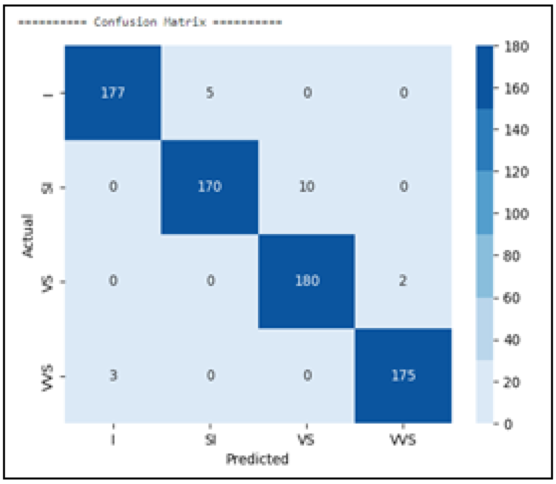

Figure 15: Confusion Matrix of clarity

4.3 Personalized gemstone recommendation

To evaluate the GRU model's performance, classification reports and confusion matrices were generated. The classification report provided precision, recall, and F1-score metrics for each gemstone class. Confusion matrices visualized the predicted versus actual gemstone classes, aiding in identifying any misclassifications.

The gemstone identification and recommendation model has an accuracy rate of 99% in recommending gemstones based on a user's description as shown in Figure 16. The model can extract relevant details from the descriptions, enabling users to find the right gemstone with ease.

```
54/54 [==============================] - 9s 93ms/step
                 precision    recall  f1-score   support

       Amethyst       1.00      1.00      1.00        44
          Agate       1.00      1.00      1.00        13
    Alexandrite       1.00      1.00      1.00        30
      Almandine       1.00      1.00      1.00        21
          Amber       1.00      1.00      1.00        47
     Bloodstone       1.00      1.00      1.00        14
      Carnelian       1.00      1.00      1.00        32
      Cat's-Eye       1.00      1.00      1.00        10
Black Chalcedony      1.00      1.00      1.00         7
     Chalcedony       1.00      1.00      1.00        21
        Citrine       1.00      1.00      1.00        49
          Coral       1.00      0.95      0.98        22
        Emerald       1.00      1.00      1.00        41
       Hematite       1.00      1.00      1.00        60
      Hessonite       1.00      1.00      1.00        22
         Iolite       1.00      1.00      1.00        34
           Jade       1.00      1.00      1.00        47
        Kunzite       1.00      1.00      1.00        29
      Moonstone       1.00      1.00      1.00        43
      Morganite       1.00      1.00      1.00        39
    Rose Quartz       1.00      1.00      1.00        40
           Ruby       1.00      1.00      1.00        60
...
       accuracy                           0.99      1720
      macro avg       0.84      0.86      0.84      1720
   weighted avg       0.98      0.99      0.99      1720
```

Figure 16: Classification Report of GRU model

Figure 17's confusion matrix shows the accurate classification of gemstones across categories.

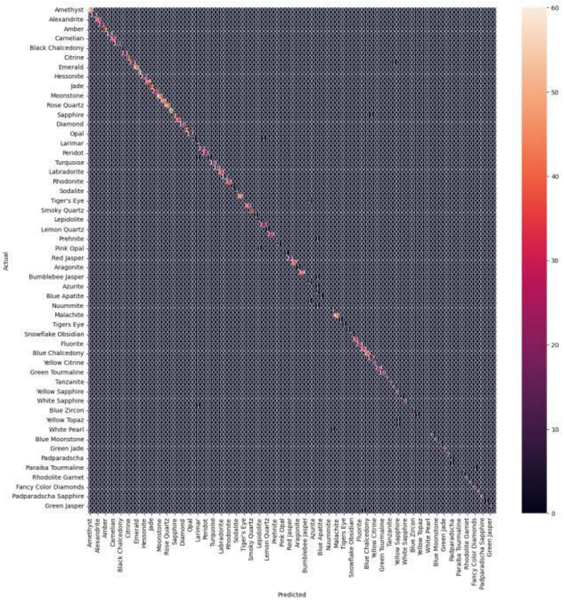

Figure 17: Confusion Matrix of GRU model

Figure 18's histogram displays gemstone description's token length distribution, revealing data nature and tokenization effectiveness.

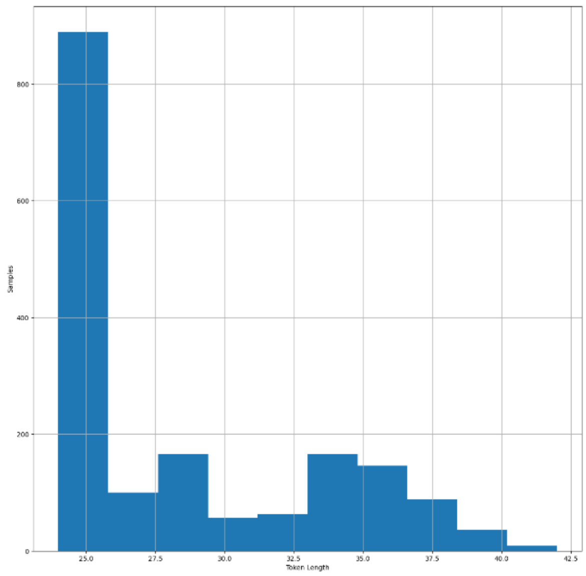

Figure 18: Token length of dataset

4.4 Price Prediction of Gemstones

The evaluation of the model's performance was an important assignment in the context of the findings of this study and the discussion that followed. The Root Mean Squared Error (RMSE), which was a crucial factor in determining the degree of variation between expected and observed prices, emerged as a key metric. The current study revealed an impressive calculated RMSE value of 15753.3155, which attests to the model's skill in accurately predicting gemstone prices.

ISSN (online): 2581-3048
Volume 7, Issue 10, pp 406-416, October-2023
https://doi.org/10.47001/IRJIET/2023.710054

Figure 19 shows the comparison between actual values and predicted values of the gemstones. This accomplishment highlights both the effectiveness of the selected regression technique.

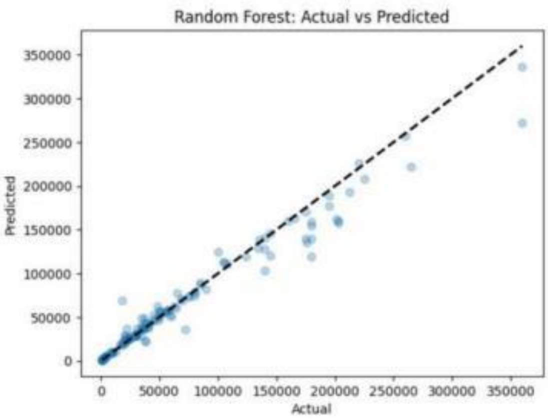

Figure 19: Comparison between actual and predicted values

V. CONCLUSION

The "Gemo" project, which combines cutting-edge technologies like artificial intelligence (AI), machine learning (ML), 3D computer vision, and natural language processing (NLP), offers a ground-breaking strategy for transforming the gemstone industry. The project addresses several significant issues faced by the sector, such as subjective color and cut prediction, a dearth of customized recommendations, and the requirement for accurate pricing mechanisms. The creation of an artificial intelligence (AI)-driven mobile application is how "Gemo" provides a complete answer for the gemstone sector. Through image processing and recognition, it improves the detection of color and clarity, eliminates subjectivity in cut prediction, offers customized gemstone recommendations using NLP, and makes precise price predictions based on gemstone characteristics. Additionally, "Gemo" boosts efficiency, fair pricing, and transparency, minimizing the industry's reliance on human labor and the effect of bias and mistakes caused by people. This research project offers standardized, data-driven approaches that not only enhance the quality of gem analysis but also the overall customer experience, representing a significant advancement for the gemstone industry. "Gemo" has the potential to change the industry by changing modern computer-based methods for old human-based ones, making it more dynamic, competitive, and customer-focused. Future work for the "Gemo" project entails refining gemstone color and clarity detection through a more diverse dataset, improving the user interface, implementing real time updates, and incorporating a feedback loop for model refinement. Additionally, exploring blockchain integration for transparent transactions, expanding the application's reach, and addressing ethical considerations regarding workforce impact are essential steps for the project's continued success and industry transformation.

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International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 10, pp 406-416, October-2023

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International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 10, pp 406-416, October-2023

https://doi.org/10.47001/IRJIET/2023.710054

Citation of this Article:

Senarathne K.A.N.S, Epitawatta E.A.E.K, Thennakoon K.T, Diunugala M.W, H.M. Samadhi Chathuranga Rathnayake, M. Pipuni Madhuhansi, "“Gemo”: An AI-Powered Approach to Color, Clarity, Cut Prediction, and Valuation for Gemstones" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 10, pp 406-416, October 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.710054

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