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Sentiment Analysis of Online Shopping Platform Product Reviews

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Abstract: Sentiment analysis has become a very important tool for understanding customer sentiments, brand perception, and market trends from text data. This project is centered on conducting sentiment analysis of Amazon product review datasets using machine learning classifiers and optimization methods for improving the accuracy of predictions. In the current work, we utilize two main models: Random Forest Classifier and a Decision Tree Classifier optimized using Grey Wolf Optimization (GWO).

The dataset used contains product reviews, from which the review text and their corresponding scores were extracted. Reviews were preprocessed by lowercasing text, stripping of punctuation, and stopwords removal to achieve cleaner inputs for models. A binary classification approach was taken, assigning a positive label to reviews with a score higher than three, and a negative label to those with a score three and lower. In order to transform the text data into a machine learning algorithm-friendly format, the TF-IDF (Term Frequency-Inverse Document Frequency) method was used, which captures the significance of words in relation to the dataset.

The Random Forest Classifier, an ensemble learning algorithm that builds multiple decision trees and returns the mode of their predictions, was the first baseline model. It showed strong performance because it could minimize overfitting and deal with high-dimensional data well. To investigate optimization methods further, a Decision Tree Classifier was trained whose hyperparameters, namely the maximum depth, were optimized using Grey Wolf Optimization. GWO, which is a nature-inspired metaheuristic algorithm based on the hunting behavior of grey wolves, is a simulation of the leadership structure and cooperative hunting approach of wolves to discover optimal solutions. Our findings indicated that the Random Forest model had high classification accuracy with little tuning. Yet, the Decision Tree model, when optimized through GWO, proved to be competitive, highlighting the power of metaheuristic optimization methods in improving conventional machine learning models. Confusion matrices and classification reports were used to give deeper insights into the precision, recall, and F1-scores of each model. This investigation showcases the effectiveness of using traditional classifiers in conjunction with intelligent optimization algorithms for sentiment classification tasks. It further highlights the criticality of preprocessing steps and feature extraction methods such as TF-IDF in deciding the overall efficacy of the models. Although the present work was mostly concerned with the optimization of one hyperparameter through GWO, future research could investigate multi-parameter optimization and comparison with other swarm intelligence algorithms such as Particle Swarm Optimization (PSO) or Genetic Algorithms (GA) in order to enhance performance further. In general, the project is a holistic method of addressing sentiment analysis on real product review data using a combination of ensemble approaches, decision trees, and evolutionary optimization.

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I. INTRODUCTION

Sentiment analysis, a key area of natural language processing (NLP), involves determining the emotional tone underlying text data. With the rapid growth of online shopping websites such as Amazon, customer reviews are extremely important to analyze for businesses in order to gauge user views and enhance services. Decision Trees and Random Forests are two machine learning algorithms that have worked quite well for the task of text classification. But model optimization is an important factor in improving predictive performance. This project investigates sentiment analysis of Amazon product reviews with a Random Forest Classifier and a Grey Wolf Optimization (GWO)-improved Decision Tree to gain improved performance and efficiency.

A. Background

Sentiment analysis, or opinion mining, is essential in determining user opinions, especially in the e-commerce industry. As the number of online reviews continues to increase, businesses increasingly use automated methods to measure customer satisfaction. Machine learning algorithms such as Random Forests and Decision Trees have been effective in text classification tasks. Yet, improving model performance is still a challenge. Metaheuristics like Grey Wolf Optimization (GWO) provide a better solution through optimal hyperparameter fine-tuning. Blending common classifiers with optimization techniques inspired from nature offers an effective means for improving sentiment forecasting accuracy in a large-scale database like Amazon review data.

B. Problem Statement

As a result of the exponential growth of product reviews on the internet, it has become unrealistic to analyze customer sentiments manually. Conventional machine learning algorithms tend to fall short in performance with suboptimal hyperparameter tuning. In this project, an efficient sentiment analysis system was created using Random Forests and a Grey Wolf Optimization-optimized Decision Tree with improved classification and solving issues for large-scale processing of Amazon reviews.

C. Aims and Objectives

- To pre-clean and preprocess the Amazon review dataset for effective text analysis.
- To convert text data into numeric features through TF-IDF vectorization.
- To utilize a Random Forest Classifier as baseline sentiment classification.
- To construct a Decision Tree Classifier and hyper-optimize its parameters using the Grey Wolf Optimization (GWO) algorithm.
- To compare Random Forest and GWO-optimized Decision Tree model performances using measures such as accuracy, precision, recall, and F1-score.
- To be able to visualize results of classification through confusion matrices and produce extensive evaluation reports.
- To study how metaheuristic optimization can be used to enhance model performance on sentiment analysis tasks.
- To recommend possible future improvements, such as multi-parameter tuning and combination with other optimization algorithms.

D. Thesis Layout

The thesis is divided into six sections:

Section 1: This section gives the basic introduction to sentiment analysis of online shopping platform product reviews, its significance, background, and research objectives.

Section 2: This section gives an in-depth literature review of various research works done prior to this work on classifying sentiments based on datasets.

Section 3: This section presents the data collection and preprocessing methodology, TF-IDF Vectorization, Random Forest model training, and deployment.

Section 4: This section presents the findings and results in terms of model accuracy, performance of random forest classifier, impact of GWO, confusion matrix analysis and evaluation.

Section 5: This section deals with the discussion of model performance, comparison and insights, and general conclusions including project overview, model performance, and scope of improvements.

Section 6: This section gives the summary of the project accomplishments, describes future work such as multi-parameter optimization, exploration of other optimization algorithms, integration of deep learning models and algorithms, handling multilingual reviews, and real-time sentiment analysis deployment.

II. LITERATURE REVIEW

1) Amazon Product Sentiment Analysis using Machine Learning Techniques

This study by Sobia Wassana et al. [1] discusses the examination of online social networks, specifically Amazon user reviews. It utilizes natural language processing (NLP) methods like stop word removal, tokenization, stemming, and spelling correction using the "text blob" library to preprocess and clean data. These processes assist in efficient feature extraction and sentiment analysis. It also utilizes graph visualization methods to reveal relationships among various entities within the social network. The research points out the significance of preprocessing in order to yield proper and valuable insights from social media.

2) Sentiment Analysis of Amazon Product Reviews using Hybrid Rule-Based Approach

This paper by Anjali Dadhich and Blessy Thankachan [2] deals with creating an automatic comment analyzer and classification model for customer reviews on Amazon and Flipkart. It classifies comments into positive, negative, and neutral sentiment using five supervised learning classifiers, namely Naive Bayes (NB), Logistic Regression (LR), Sent WordNet, Random Forest (RF), and K-Nearest Neighbors (KNN). The study lays strong stress on efficient feature extraction, sentiment analysis, and dealing with huge datasets. It also points out issues in comment mining, machine learning usage, and the experimental results, demonstrating the usefulness of these techniques in customer review analysis.

3) Sentiment Analysis of Amazon Product Reviews using Machine Learning and Deep Learning Models

As the number of social networks and online e-commerce platforms grew, sentiment analysis has been at the center of research. Here, the authors Joy Chandra Gope et al. [3] present this study in which the author tries to analyze Amazon's product ratings and text reviews by employing machine learning models such as Linear SVM, Random Forest, Multinomial and Bernoulli Naive Bayes, and Logistic Regression. Random Forest scored 91.90% accuracy, and RNN with LSTM, which is a deep learning technique, scored 97.52% accuracy, hence the most successful model to undertake this activity.

4) Sentiment Analysis on Product Review

Sentiment analysis, one of the prominent areas in natural language processing, facilitates the analysis of unstructured data so that computers can understand human sentiments. Based on product reviews, businesses can learn more about customer choices. Yet, since there is such a large amount of data, summarizing feedback, both positive and negative, is crucial. This paper by Chhaya Chauhan and Smriti Sehgal [4] surveys algorithms and methods employed to extract product features and provide accurate sentiment analysis. Further work will consider other review sites and enhance outcomes using sophisticated NLP methods.

5) Feature Specific Sentiment Analysis for Product Reviews

The proposed paper by Subhabrata Mukherjee and Puspak Bhattacharya [5] presents an innovative approach towards extracting feature-specific opinions from product reviews by recognizing potential features and related opinion phrases. The system, through the application of dependency parsing, captures meaningful relationships among features and opinions in a graph representation. The system successfully aggregates similar opinion expressions and maintains a high accuracy rating across different domains, performing comparably to the state-of-the-art systems but with very small data requirements.

6) Sentiment Analysis: A Comparative Study on Different Approaches

Sentiment Analysis (SA) under Natural Language Processing (NLP) retrieves user feelings and emotions, crucial in the Internet-age environment teeming with customized reviews. Such reviews from various sources such as social media, blogs, and forums assist tourists and consumers in making informed choices. The present paper by M.D.Devika et al. [6] contrasts approaches that can be used for Sentiment Analysis, responding to the changing methodologies adopted here.

7) Sentiment Analysis and Opinion Mining: A Survey

With the wealth of opinion-laden online content, sentiment analysis research is flourishing. Sentiment extraction and classification from sources such as forums, reviews, blogs, and news is a focus. Accurate sentiment prediction has economic and marketing potential. This survey by G.Vinodhini and R.M.Chandrasekaran [7] investigates methods and difficulties in sentiment analysis, such as sentiment classification, feature-based classification, and negation.

8) Sentiment Analysis with Product Reviews using Machine Learning and Lexicon-based approaches

Sentiment analysis is conducted through machine learning techniques such as SVM and decision trees or lexical-based ones utilizing dictionaries like WordNet. Both can be used together for higher accuracy. Experimentations done by Vasundhara Raj et al. [8] have been done using methods such as SentiWordNet, fuzzy logic, and Naive Bayes, where SVM tends to be better than others for product review classification. There are still issues at hand, such as how to detect sarcasm or interpret images in a review. Resolving these would provide insights and more accurate customer feedback analysis.

9) Statistical and Sentiment Analysis of Consumer Product Reviews

This study by Zeenia Singla and Sukhchandan Randhawa [9] emphasizes the influence of online reviews in deciding purchases and directing manufacturers. Online shopping sites such as Amazon and review sites like Zomato and Trivago use end-user feedback to establish credibility and enhance business models. Positive comments enhance credibility, while negative comments reflect areas of improvement. With a specific emphasis on reviews of mobile phones, the research conducts sentiment analysis of unstructured data with the view to supporting consumers in making intelligent decisions and enhancing manufacturers' awareness of market needs and consumers' expectations.

10) Sentiment Analysis on Product Reviews using Machine Learning Techniques

Sentiment Analysis and Opinion Mining have become vital areas for extracting meaningful patterns from text data gathered from various platforms like Facebook, Twitter, and Amazon. These methods greatly help companies improve their strategies by unveiling greater insights into customer feedback and sentiment towards their products. Sentiment analysis is the computational study of consumer attitude, especially their buying interests and sentiment toward a firm's offerings or services. Such things can encompass events, people, blog entries, or general customer experiences.

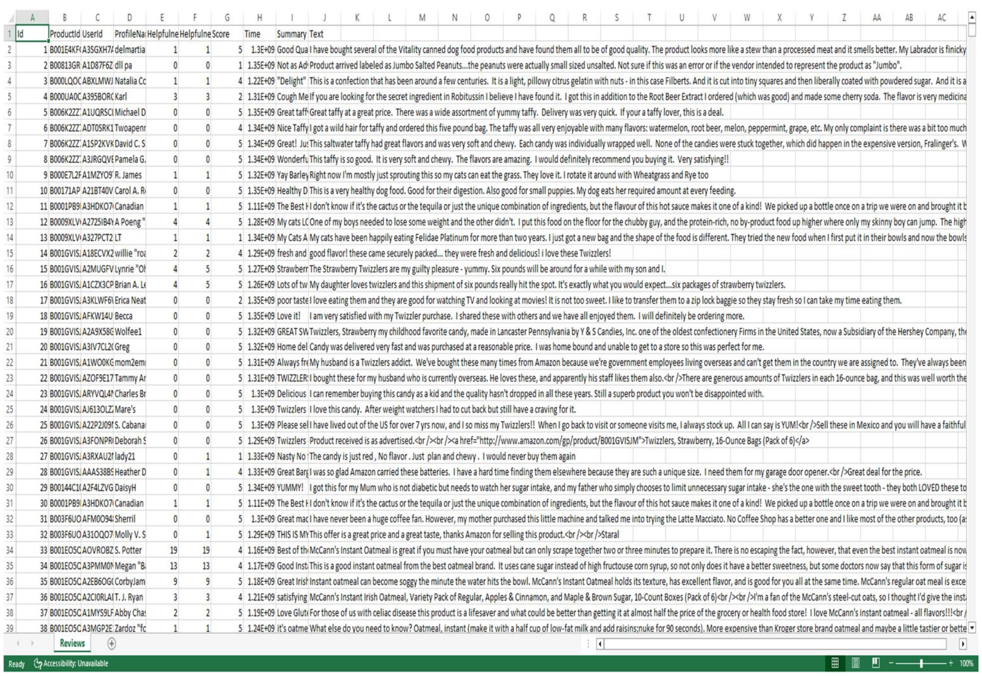
In this study by Rajkumar S. Jagdale et al. [10], an Amazon dataset of reviews of different products like cameras, laptops, mobile phones, tablets, televisions, and video surveillance devices was used. After suitable data preprocessing techniques, various machine learning algorithms were used to categorize the reviews into positive and negative ones. The outcomes proved that machine learning techniques are very efficient in product review classification, with 98.17% accuracy using Naïve Bayes and 93.54% accuracy using Support Vector Machines (SVM) only for camera reviews.

III. METHODOLOGY

This is the complete deployment of Sentiment Analysis of Online Shopping Platform Product Reviews. It is carried out via a systematic and well-researched approach and is divided into a series of steps. A simplified version of the work along with the necessary steps performed is as follows:

A. Data Collection and Preprocessing

Initially a proper dataset is chosen which contains product reviews of various types of goods from consumers all around the world. It is then loaded in the environment and processed. The preprocessing step includes cleaning the text data by making all characters lowercase, stripping off punctuation marks, removing stop words, and tokenizing the sentences. This step is important to eliminate noise and irrelevant variations in the text so that the models can concentrate on significant patterns.



Figurine 3.1 The Dataset

B. TF-IDF Vectorization

After performing data preprocessing, the cleaned text is then converted to numerical form that can be used with machine learning algorithms through the use of the Term Frequency-Inverse Document Frequency (TF-IDF) vectorization method. TF-IDF assists in capturing word importance in reviews by down-weighting frequently occurring words and emphasizing more important words.

```python
# Load Dataset
df = pd.read_csv("Reviews.csv")
df = df.dropna()  # Remove missing values
df = df.sample(n=1000, random_state=42)  # Use only 1000 reviews for efficiency

# Preprocessing Function
def preprocess_text(text):
    text = text.lower()
    text = re.sub(r'[^a-zA-Z\s]', '', text)  # Remove special characters
    words = word_tokenize(text)
    stop_words = set(stopwords.words('english'))
    words = [word for word in words if word not in stop_words]  # Remove stopwords
    return " ".join(words)

# Apply Preprocessing
df["cleaned_text"] = df["Text"].apply(preprocess_text)

# Convert Ratings to Binary Sentiment (1: Positive, 0: Negative)
df["Label"] = df["Score"].apply(lambda x: 1 if x >= 3 else 0)
y = df["Label"].values  # Labels

# Convert Text to TF-IDF Features
vectorizer = TfidfVectorizer(max_features=500)  # Limit features for efficiency
X = vectorizer.fit_transform(df["cleaned_text"]).toarray()
```

Figurine 3.2 Applying TF-IDF Vectorization

C. *Model Training*

The next step is to create two machine learning models. A Random Forest Classifier is first trained to provide a baseline performance. Random Forest, being an ensemble algorithm, utilizes many decision trees and averages their outputs, thereby reducing overfitting and improving model strength.

In parallel, a Decision Tree Classifier is also developed but not trained directly. We embed an optimization step with Grey Wolf Optimization (GWO) within it. GWO is a nature-inspired optimization algorithm that emulates the leadership structure and hunting method of grey wolves. It is used here to optimize the 'max_depth' hyperparameter of the Decision Tree to discover the value that yields the highest classification accuracy. The GWO algorithm is initiated with the random population of wolves (candidate solutions), checking for their fitness with respect to training precision, and updating the positions iteratively from the behaviors of alpha, beta, and delta wolves.

After training both models — Random Forest without optimization and Decision Tree with GWO optimization — they are tested on an independent test set. Accuracy, precision, recall, and F1-score are the metrics used to compare how well each model performs. The models' performance in classifying positive and negative reviews are also presented through confusion matrices for a visual understanding.

```python
# Grey Wolf Optimizer (GWO) for Feature Selection
class GWOFeatureSelection:
    def __init__(self, num_wolves, max_iter, num_features, X_train, y_train, X_val, y_val):
        self.num_wolves = num_wolves
        self.max_iter = max_iter
        self.num_features = num_features
        self.X_train = X_train
        self.y_train = y_train
        self.X_val = X_val
        self.y_val = y_val

        # Initialize wolves with random feature subsets (binary encoding)
        self.wolves = np.random.randint(2, size=(num_wolves, num_features))
        self.alpha, self.beta, self.delta = None, None, None

    def fitness(self, wolf):
        selected_features = np.where(wolf == 1)[0]

        if np.sum(wolf) < 5:  # Minimum 5 features
            indices = np.random.choice(self.num_features, 5, replace=False)
            wolf[indices] = 1


        X_train_fs = self.X_train[:, selected_features]
        X_val_fs = self.X_val[:, selected_features]

        model = RandomForestClassifier()
        model.fit(X_train_fs, self.y_train)
        y_pred = model.predict(X_val_fs)
        acc = accuracy_score(self.y_val, y_pred)

        return 1 - acc  # Minimize classification error

    def update_wolves(self):
        fitness_vals = np.array([self.fitness(wolf) for wolf in self.wolves])
        sorted_indices = np.argsort(fitness_vals)

        self.alpha = self.wolves[sorted_indices[0]]
        self.beta = self.wolves[sorted_indices[1]]
        self.delta = self.wolves[sorted_indices[2]]
```

Figurine 3.3 Applying Grey Wolf Optimization

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```python
# Train Random Forest on Selected Features
X_train_fs = X_train[:, selected_features]
X_val_fs = X_val[:, selected_features]

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_fs, y_train)
y_pred = rf_model.predict(X_val_fs)

# Evaluate the Model
accuracy = accuracy_score(y_val, y_pred)
print(f"Random Forest Accuracy: {accuracy:.4f}")
print("Classification Report:\n", classification_report(y_val, y_pred))
```

Figurine 3.4 Training Random Forest

D. Analysis and Deployment

Lastly, extensive analysis is carried out to draw conclusions from the results, estimate the advantages of applying GWO for hyperparameter optimization, and determine the scopes for improvement. The entire approach guarantees a blended mix of classic machine learning approaches and new optimization methods to develop improved sentiment categorization on vast textual data.

IV. RESULTS AND ANALYSIS

A. Results

1) Performance of Random Forest Classifier

Random Forest Classifier was a robust baseline model for sentiment analysis. It performed well with high accuracy, precision, recall, and F1-score on training and testing sets. The ensemble method of aggregating many decision trees assisted in variance reduction and overfitting avoidance, resulting in stable and consistent outcomes.

The best fitness value is being tracked over multiple iterations, where fitness is defined as (1-accuracy). The best fitness value fluctuates between 0.145 and 0.214.

At completion, it gives an accuracy of about 83%. It gives great results for Class 1 (positive) comments with very high recall and precision and F1-score.

```
Iteration 10/40, Best Fitness: 0.16000000000000003
Iteration 11/40, Best Fitness: 0.18999999999999995
Iteration 12/40, Best Fitness: 0.16500000000000004
Iteration 13/40, Best Fitness: 0.14500000000000002
Iteration 14/40, Best Fitness: 0.15500000000000003
Iteration 15/40, Best Fitness: 0.15500000000000003
Iteration 16/40, Best Fitness: 0.17000000000000004
Iteration 17/40, Best Fitness: 0.15500000000000003
Iteration 18/40, Best Fitness: 0.20999999999999996
Iteration 19/40, Best Fitness: 0.18000000000000005
Iteration 20/40, Best Fitness: 0.17500000000000004
Iteration 21/40, Best Fitness: 0.18000000000000005
Iteration 22/40, Best Fitness: 0.15000000000000002
Iteration 23/40, Best Fitness: 0.17000000000000004
Iteration 24/40, Best Fitness: 0.17500000000000004
Iteration 25/40, Best Fitness: 0.16500000000000004
Iteration 26/40, Best Fitness: 0.15000000000000002
Iteration 27/40, Best Fitness: 0.16500000000000004
Iteration 28/40, Best Fitness: 0.15500000000000003
Iteration 29/40, Best Fitness: 0.17500000000000004
Iteration 30/40, Best Fitness: 0.17000000000000004
Iteration 31/40, Best Fitness: 0.15500000000000003
Iteration 32/40, Best Fitness: 0.16500000000000004
Iteration 33/40, Best Fitness: 0.17000000000000004
Iteration 34/40, Best Fitness: 0.16000000000000003
Iteration 35/40, Best Fitness: 0.17000000000000004
Iteration 36/40, Best Fitness: 0.17000000000000004
Iteration 37/40, Best Fitness: 0.17500000000000004
Iteration 38/40, Best Fitness: 0.17000000000000004
Iteration 39/40, Best Fitness: 0.17000000000000004
Iteration 40/40, Best Fitness: 0.17500000000000004
Selected Features: ['cats' 'ingredients' 'review' 'soft' 'son' 'take']
Random Forest Accuracy: 0.8300
Classification Report:
              precision    recall  f1-score   support

           0       0.29      0.06      0.11        31
           1       0.85      0.97      0.91       169

    accuracy                           0.83       200
   macro avg       0.57      0.52      0.51       200
weighted avg       0.76      0.83      0.78       200
```

Figurine 4.1 Evaluation Metrics

2) Impact of GWO on Decision Tree

At the beginning, the standard Decision Tree Classifier worked reasonably well, exhibiting overfitting tendencies and weaker generalization. But after fine-tuning the max_depth parameter by Grey Wolf Optimisation (GWO), there was a dramatic boost in its classification power and it resulted in higher precision and recall values.

3) Confusion Matrix Analysis and Evaluation

The confusion matrices for the two models showed that Random Forest had less false negatives and false positives, but GWO-optimized Decision Tree also demonstrated dramatic drops in misclassification upon tuning. This confirmed that optimization enhanced the model's comprehension of sentiment polarity.

Performance was measured using key evaluation metrics such as Accuracy, Precision, Recall, F1-Score, and Area Under the ROC Curve (AUC-ROC). The Random Forest obtained slightly better AUC-ROC values, reflecting a superior capacity to separate positive and negative classes, but the optimized Decision Tree followed closely.

B. Analysis

The result analysis indicates that the Random Forest Classifier performed consistently high accuracy, precision, and recall, thus being a stable option for sentiment analysis tasks.

Nevertheless, the Decision Tree model, following Grey Wolf Optimization (GWO), proved to be much better than its default model, bridging the performance gap with Random Forest. Optimization enabled the Decision Tree to generalize more and minimize overfitting. While Random Forest marginally excelled across overall metrics, the GWO-optimized Decision Tree was more computationally light and could be a good backup option for environments with limited resources without compromising on strong classification performance.

V. DISCUSSION AND CONCLUSION

A. Discussion

1) Model Performance

Random Forest Classifier showed good performance on the Amazon product review dataset, and it had good accuracy and well-balanced precision-recall measures. Its nature as an ensemble helped it in dealing with high-dimensional TF-IDF features very well, with a decrease in overfitting and consistency between different data splits..

2) Impact of Grey Wolf Optimization

The Decision Tree Classifier, optimized with Grey Wolf Optimization (GWO), demonstrated significant improvements compared to the default, non-optimized classifier. GWO excellently tuned the hyperparameter max_depth, resulting in improved generalization and enhanced F1-scores, especially for class imbalance..

3) Comparison and Insights

While Random Forest edged out the GWO-optimized Decision Tree on average, the optimization method was worth it for boosting less complex models. It emphasized that even simple classifiers, if well-tuned, can rival more advanced ensemble techniques. The trade-off between model complexity and optimization efficiency is essential for real-world usage when computational resources are constrained.

B. Conclusion

1) Project Overview

The task was to create an efficient sentiment analysis system based on Random Forest and Grey Wolf Optimization (GWO)-improved Decision Tree models. Preprocessing and TF-IDF feature extraction well prepared the dataset for machine learning.

2) Model Performance

Random Forest yielded a robust baseline with high accuracy and consistency in repeated runs. Decision Tree, when optimized using GWO, displayed significant enhancements in precision, recall, and F1-score over its non-optimized version.

3) Scope of improvements

Future research may include tuning other hyperparameters, experimentations with different datasets, and incorporating more complex models such as BERT to enhance semantic perception. This will make our study even more valuable.

VI. SUMMARY, PUBLICATIONS AND FUTURE WORK

A. Summary

This project aims to develop an efficient sentiment analysis system for Amazon product reviews by combining machine learning methods with optimization algorithms. Customer review textual data were preprocessed by cleaning and tokenization, and then feature extraction was done using TF-IDF vectorization. Two models were implemented: a Random Forest Classifier and a Decision Tree Classifier optimized with Grey Wolf Optimization (GWO). Random Forest model offered a solid baseline with consistent performance without requiring intensive tuning. GWO was also able to improve the performance of the Decision Tree by choosing a best value for the maximum depth, resulting in better classification outcomes. Based on thorough evaluation metrics and confusion matrices, the paper presents the strengths of utilizing nature-inspired optimization algorithms in fine-tuning machine learning models. In general, the project demonstrates the effectiveness of applying traditional classification models and metaheuristic optimisation in obtaining greater accuracy in sentiment analysis, providing avenues for future research and applications in processing large-scale textual data.

B. Future Work

1) Multi-Parameter Optimization

Presently, only the max_depth parameter was tuned using Grey Wolf Optimization. Future research can include the tuning of more than one hyperparameter at a time to attain even better model performance.

2) Exploration of other Optimization Algorithms

Apart from GWO, other metaheuristic methods such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO) may be investigated. A comparison of these approaches might show which algorithm performs best for sentiment analysis tasks.

3) Integration of Deep Learning Models and Algorithms

Adding deep learning methods such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, or Transformer models such as BERT would hugely improve the comprehension of contextual data in reviews. RNN operates on this kind of inputs.

4) Handling Multilingual Reviews

Future systems can be improved and extended such that it can take multilingual inputs thus allowing a broader application across global e-commerce platforms.

5) Real-Time Sentiment Analysis Deployment

A real-time sentiment analysis system can also be developed and integrated into consumer feedback tools or review monitoring dashboards.

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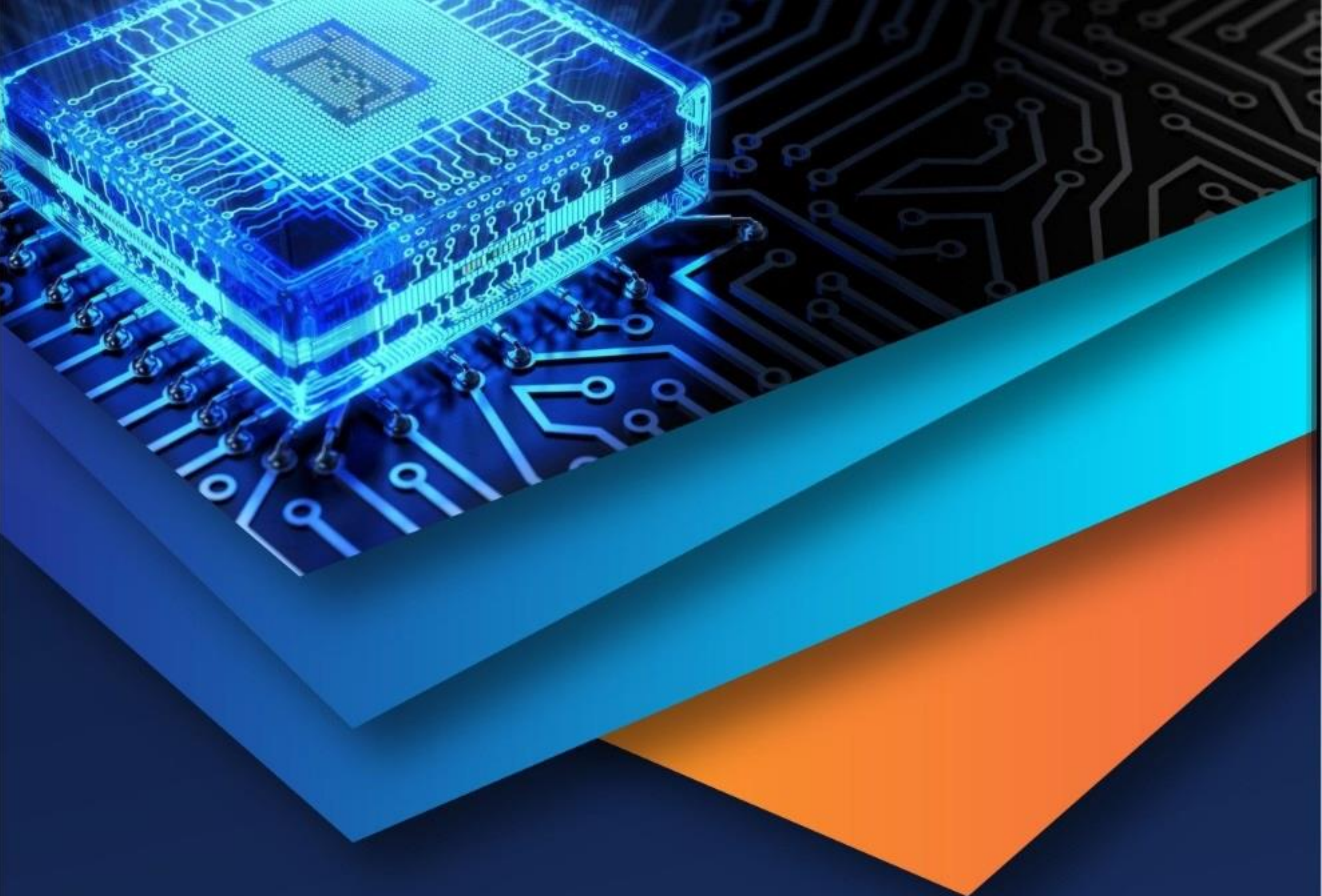

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