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ENHANCE FAKE REVIEW DETECTION: A HYBRID APPROACH OF IMPLICIT ABSA AND IMBALANCED DATASET HANDLING

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ABSTRACT

Online shopping's convenience has increased reliance on reviews, but fake reviews undermine trust in e-commerce. Many detection models analyze full review text, while overlooking subtle cues like lack of specificity, repetitive wording, and exaggerated sentiments expressed implicitly. Additionally, where genuine reviews far outnumber fake ones, dataset imbalance leads to biased machine learning models with reduced reliability. To address these challenges, this study introduces a hybrid approach integrating Implicit Aspect-Based Sentiment Analysis (ABSA) using Bidirectional Encoder Representations from Transformers (BERT) for implicit aspect extraction and Sentiment Analysis with the Synthetic Minority Over-sampling Technique (SMOTE) for handling imbalanced data. Rule-based indicators identify fake reviews, while a Support Vector Machine (SVM) with *k*-fold cross-validation evaluates performance. The dataset, sourced from Kaggle's Amazon Reviews, contains 2,852 reviews across four product categories: foods, home care, personal care, and refreshments. Before SMOTE, the average *k*-fold recall was 78%. After SMOTE, it rose to 95%, enhancing the approach's ability to detect most fake reviews despite some false positives. The final result of the constructed hybrid approach achieved 96% accuracy, 60% precision, 100% recall, and a 75% F1 score. We evaluate the performance against two comparative feature approaches, which are (i) an SVM baseline and (ii) a BERT + Rule-based + SVM without SMOTE. High recall ensures effective fake review detection, though lower precision results in some false positives. It concludes that this study enhances trust in online reviews and supports informed purchasing decisions. Future research should expand labelled datasets and explore alternative techniques like Edited Nearest Neighbors to refine the precision-recall trade-off.

Keywords: *Fake Review Detection, Sentiment Analysis, Aspect-Based Sentiment Analysis, Implicit ABSA, Imbalanced Dataset Handling, BERT, SMOTE*

1. INTRODUCTION

Online shopping has become increasingly popular due to its convenience and the wide variety of products available [1]. However, the growing reliance on online reviews has led to fraudulent practices, including fake reviews, which are deceptive evaluations meant to mislead consumers rather than reflect genuine experiences [2]. These fake reviews are often generated for financial gain, product promotion, or competitor sabotage [3].

Apart from that, research indicates that customers struggle to differentiate between genuine and fake reviews [4]. Some sellers exploit this by incentivizing customers to leave positive reviews or hiring spammers to manipulate product ratings [5]. These deceptive reviews mislead consumers and distort product credibility, making their detection crucial.

Traditional manual detection methods rely on human annotators, but studies indicate that human accuracy is only around 57% [6]. Manual detection is also time-consuming and impractical, given the rapid growth of online reviews. As a result, algorithm-based detection methods using Machine Learning (ML) have become essential [7]. ML is a branch of artificial intelligence that enables systems to learn from data and make decisions or predictions without being explicitly programmed [8]. These methods analyze textual features (e.g., language style) or behavioural features (e.g., rating patterns) [9]. Since this research focuses on Sentiment Analysis (SA), textual features are the primary consideration.

SA is a Natural Language Processing (NLP) technique that extracts subjective opinions from text [10]. It helps detect fake reviews by identifying inconsistencies in sentiment and tone [11]. SA has three levels: document level, sentence level, and aspect level. However, traditional document or sentence levels lack granularity, as it does not specify which product aspects are being praised or criticized [12].

To address this, the aspect-level technique, Aspect-Based Sentiment Analysis (ABSA), is used to detect sentiments tied to specific aspects of a product [13]. ABSA refers to the process of identifying and extracting sentiments tied to specific attributes or components of a product or service [14] and differentiates between explicit aspects, which means directly mentioned, such as *"The touchpad on my device is great, but the battery life is too short",* where "touchpad" and "battery capacity" are explicitly included in the system, indicating that they are aspects. In contrast, implicit aspects are inferred from the context, like *"This camera is elegant and quite economical"*, which implies a positive opinion on the object camera's "design" and "cost" [15]. Despite its effectiveness, implicit ABSA remains underexplored compared to explicit ABSA [16].

Another key challenge in fake review detection is the imbalance of datasets, where genuine reviews significantly outnumber fake ones [17]. Standard classifiers struggle to identify minority classes, which leads to biased models [18]. To mitigate this, techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) can balance the dataset, as it is a data augmentation that generates synthetic samples for minority classes [19].

Given these challenges, hybrid approaches combining multiple techniques offer a promising solution. Unlike single-model approaches, hybrid approaches improve accuracy, detection performance, and robustness against imbalanced data [20]. This study proposes a hybrid approach integrating implicit ABSA and imbalanced data handling to enhance fake review detection.

2. RELATED WORK

2.1 Fake Review Detection

Fake reviews are dishonest evaluations intended to manipulate product ratings and deceive customers [21]. As e-commerce grows, genuine reviews are vital in influencing purchasing decisions [22]. Research indicates that over 90% of online shoppers rely on product reviews [23], and by 2024, 95% of customers check reviews before purchasing [24]. This reliance has led some sellers to exploit the system by hiring individuals or professionals to fabricate positive reviews. The increasing interest in fake review detection requires enhancing online shopping security [25], [26].

2.2 Methods in Fake Review Detection

Researchers employ various methods in fake review detection, including Rule-Based (RB), Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Extreme Gradient Boosting (XGBOOST), Naïve Bayes (NB), K-Nearest Neighbors (KNN), Decision Tree (DT), Multinomial Naïve Bayes (MNB), Support Vector Classifier (SVC), Stochastic Gradient Descent (SGD), Bernoulli Naïve Bayes (BNB), K-Means Clustering (KMEANS), Gaussian Mixture Model (GMM), Latent Dirichlet Allocation (LDA), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP), Bidirectional Long Short-Term Memory (BiLSTM), Recurrent Neural Network (RNN), and Bidirectional Encoder Representations from Transformers (BERT).

Rule-based approaches remain useful in fake review detection, especially when researchers have limited access to labelled data. They apply predefined rules to flag suspicious reviews. Vidanagama et al. [27] achieved 88.98% accuracy using sentiment and grammatical rules, while Toplu and Liu [28] improved SVM performance to 70.12% using rule-based features. Although limited by the rigidity of their rules, these approaches are transparent and easily interpretable, making them suitable in low-resource or explainability-focused contexts. This study employs a rule-based approach as the initial component of the hybrid approach, applying sentiment score, aspect word count, and cosine similarity to identify potential fake reviews before ML classification.

Researchers have widely used traditional ML models such as SVM, RF, LR, NB, KNN, DT, and XGBoost in fake review detection. SVM

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consistently performs well, achieving up to 92.19% accuracy [25] and 85.80% to 89.75% across datasets [17], proving effective for sparse, high-dimensional data. RF and LR also show promising results, though their accuracy varies with unstructured inputs [26], [29]. NB, KNN, and DT face limitations such as overfitting and poor handling of complex language. XGBoost achieves high accuracy [30] but is resource-intensive. Considering these trade-offs, SVM offers the best balance of performance and efficiency, making it the preferred classifier in the hybrid approach.

Deep learning models such as CNN, LSTM, BiLSTM, and BERT have shown strong potential in fake review detection by capturing complex linguistic patterns. CNN-based models, including CNN-LSTM hybrids, achieved up to 95.5% accuracy [31], while LSTM and BiLSTM reached 93.09% and 90.1%, respectively [32], [33]. BERT showed varying results, from 63% to 90.94% [29], [34], but performed better when combined with other models. Despite their accuracy, deep learning models require large, labelled datasets and high computational resources, making them unsuitable for identifying and classifying fake reviews. However, this study employs BERT for implicit ABSA, leveraging its contextual strength to enhance the hybrid approach's ability to detect subtle fake reviews and their underlying sentiments.

Hybrid and ensemble approaches have gained attention for improving fake review detection by combining the strengths of multiple models. Liu et al. [35] integrated CNN, BiLSTM, attention mechanisms, and behavioral features, achieving up to 91% accuracy. Duma et al. [1] reported 99.5% accuracy using a hybrid of BERT, CNN, LSTM, and emotional features, showing the benefits of combining contextual, sequential, and affective cues. While these approaches often require significant computational resources and tuning, they are worthwhile in this research context as fake reviews are complex and subtle, often requiring both linguistic pattern recognition and semantic understanding. This study proposes a hybrid approach integrating rule-based indicators for identifying fake reviews and SVM for classification, offering a balanced solution between accuracy, efficiency, and interpretability. Additionally, the approach employs BERT for implicit ABSA, leveraging its contextual understanding to enhance sentiment detection.

2.3 Sentiment Analysis

SA, or opinion mining, is an NLP subfield that extracts subjective text information. It classifies sentiments as positive, negative, or neutral [36]. In fake review detection, SA helps analyze reviews' tone and emotional content to identify patterns indicative of fake reviews [11].

Researchers conduct sentiment analysis (SA) at three levels: document level, sentence level and aspect level. The document-level classifies overall sentiment, while the sentence level detects mixed sentiments within a text [37], [38]. At a finer level, the aspect level focuses on sentiment related to specific product or service aspects. This approach requires NLP techniques to identify aspects and evaluate opinions associated with them [39].

Thus, ABSA detects entities and aspects before analyzing the opinions expressed about them [36]. Aspects can be either explicit, directly mentioned in the text, or implicit, requiring inference from the context. [15]. Since implicit aspects lack direct mention, implicit ABSA is essential for identifying them, making it a suitable approach for this study.

2.4 Methods in Implicit ABSA

Researchers use various methods to enhance implicit ABSA, including SVM, LDA, Supervised Latent Dirichlet Allocation (SLDA), KNN, BERT, SenticNet, NB and RF. Benarafa et al. [40] improved SVM with different kernels, achieving 93.42% accuracy, while George and Srividhya [19] combined LDA with ensemble methods, reaching 96.1% accuracy. Fu et al. [41] used contrastive learning and knowledge embedding, attaining 89.78% accuracy. BERT has outperformed traditional methods, with Van Hee et al. [42] reporting 74% accuracy, surpassing SVM (72%).

Traditional models such as LDA and KNN, though widely adopted for topic modeling and classification, exhibit limitations when applied to implicit aspect extraction. LDA, for instance, tends to overlook co-occurrence relationships and lacks the ability to capture bidirectional contextual cues [43], which are critical in identifying implicit sentiments. Similarly, KNN suffers from the curse of dimensionality in high-dimensional feature spaces [44], reducing its reliability in text-rich environments.

In contrast, BERT's deep bidirectional encoding and pre-trained language representations make it a robust model for capturing complex,

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context-dependent patterns in text. While models like LSTM and CNN offer deep learning alternatives, they often fall short in either long-range dependency retention (LSTM) or global context comprehension (CNN), as noted by [12] and [34]. Additionally, these models generally offer lower interpretability, which can be a limitation in fake review detection applications where transparency is desirable [45].

Therefore, this study selects BERT for its strong performance metrics across various NLP tasks. It has also demonstrated an ability to effectively handle nuanced language and implicit sentiment. These strengths make it an ideal choice for the implicit ABSA task in this study.

2.5 Imbalanced Dataset

In ML, imbalanced data occurs when one class has significantly fewer instances than another, often making minority class prediction more challenging [18]. The majority classes have more samples, while minority classes have fewer but are usually more critical for prediction [46]. Ignoring class imbalance can lead to biased models, making it essential to address this issue for accurate and reliable predictions [47].

2.6 Techniques for Imbalanced Dataset

Previous research has employed four main techniques for handling imbalanced datasets in fake review detection which are resampling [17], [23], [48], [49], SMOTE [50], evaluation metric [29], [51], and data collection [46], [52]. While collecting more data can improve minority class representation, it is often impractical due to time, cost, and scalability limitations. Resampling methods, such as oversampling and undersampling, offer more accessible solutions but come with trade-offs. Oversampling may lead to overfitting by duplicating patterns in the minority class, whereas undersampling can discard essential data from the majority class, potentially reducing generalization performance.

In contrast, SMOTE addresses these limitations by generating synthetic examples for the minority class, producing a more balanced dataset without duplicating data or discarding useful information. Saxena et al. [50] demonstrated its effectiveness by increasing Light Gradient Boosting Machine (LightGBM) accuracy from 62.5% to 85.72% and RF from 65.2% to 81.8%. SMOTE improves model accuracy and robustness in fake review detection by enhancing class representation without compromising data integrity. Hence, this research adopts SMOTE to handle dataset imbalance within the constructed hybrid approach.

3. RESEARCH METHOD

3.1 Data Collection

This study uses the Amazon reviews dataset. It comprises 2852 data points, a comprehensive feedback collection across various Amazon-branded products [53]. The dataset contains categories such as foods, home care, personal care, and refreshments. Following data collection, the study divides the dataset into training and testing subsets to facilitate model development and evaluation. An 80/20 split divides the dataset into a training subset (2,066 data) and a testing subset (516 data). After splitting the original dataset into two subsets, the approach applies a 90/10 split further to divide the training data into training and validation sets. Specifically, we manually labelled 10% (207) of the 2066 training data.

3.2 Pre-processing Dataset

Pre-processing the downloaded dataset ensures its suitability as input for the developed hybrid approach. The data pre-processing phase consists of three essential steps: data labelling, data cleaning and text pre-processing.

3.2.1 Data labelling

Data labelling is essential in pre-processing to ensure accurate annotation for effective model training. This process involved manual labelling of implicit terms and aspects, review separation based on these aspects and sentiment labelling. This enhances the model's learning and classification accuracy.

3.2.2 Data cleaning and text pre-processing

The dataset undergoes cleaning and pre-processing to remove inconsistencies like garbled text and excessive whitespaces while preserving BERT's contextual information. The approach avoids stop word removal and stemming to preserve semantic richness. Pre-processing includes tokenization, padding, attention mask creation, and sentiment label encoding to structure data for efficient model training.

3.3 Constructing Hybrid Approach to Enhance Fake Review Detection

As shown in Figure 1, the hybrid approach (red dashed border) integrates BERT and SMOTE (blue dashed border) to enhance fake review detection through contextual understanding (implicit ABSA) and imbalanced dataset handling. A rule-based indicator detection process (green dashed border) further aids in identifying fake reviews.

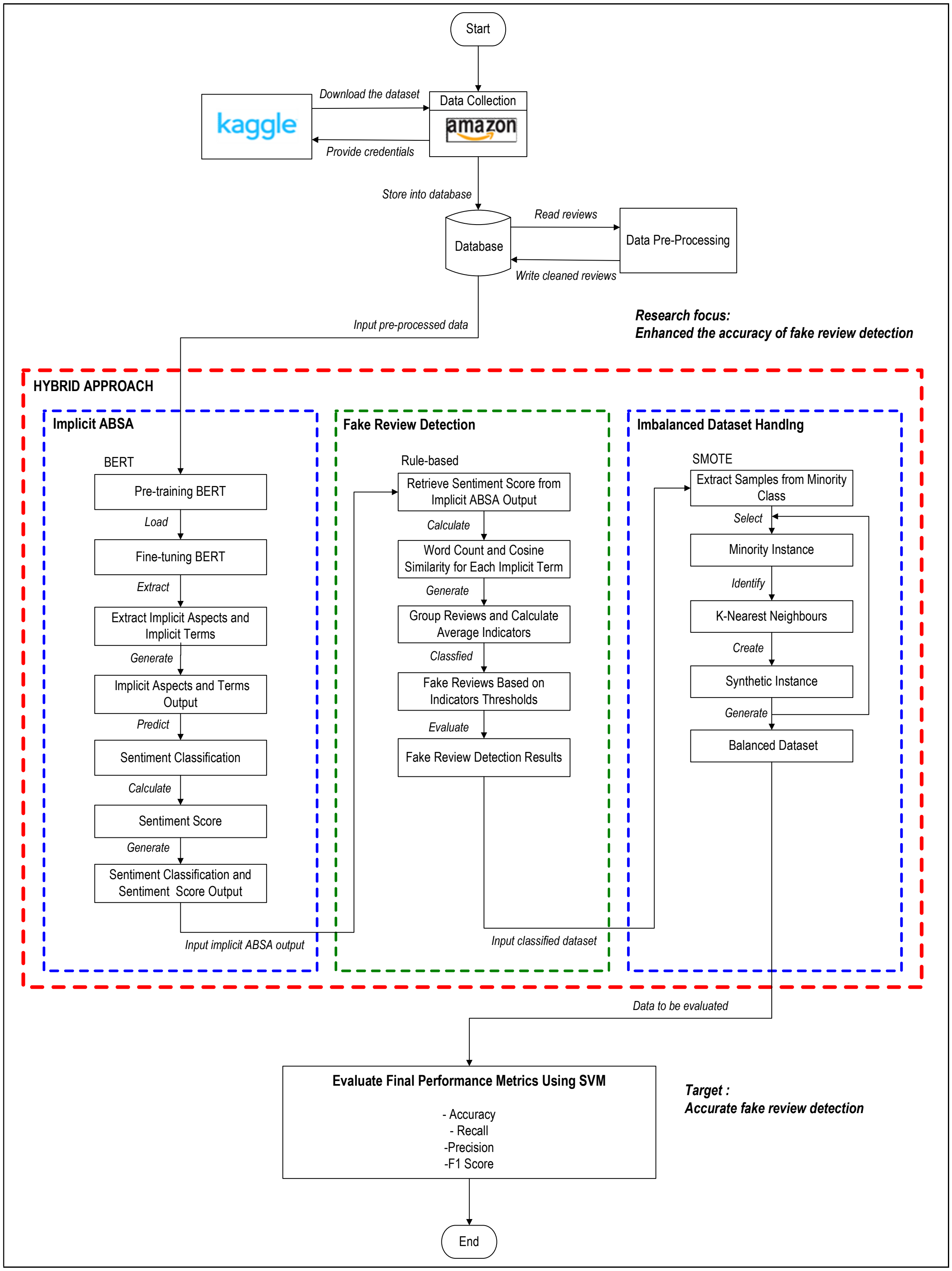

Figure 1: Research Hybrid Approach to Enhance Fake Review Detection

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3.3.1 Implicit aspect extraction and sentiment analysis

Data retrieval is the first step in preparing for implicit aspect extraction and SA. Figure 2 illustrates the implicit ABSA process within the hybrid approach derived from the previous Figure 1. The BERT model, initialized using Hugging Face's transformers library, is pre-trained for sequence classification. This study selects Hugging Face for its pre-trained models and user-friendly tools that streamline text processing and classification. The approach loads the pre-trained 'Bert-base-uncased' model to classify sentiments as positive, negative, or neutral.

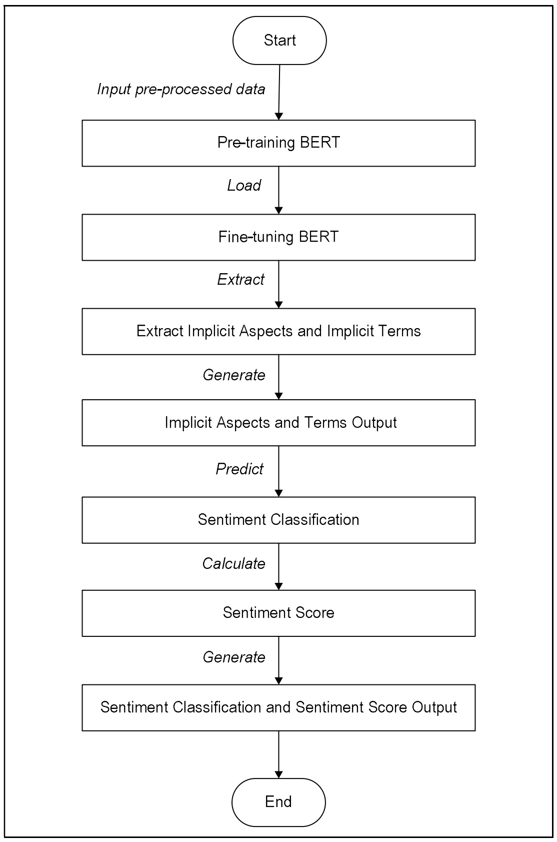

Figure 2: Flowchart for Implicit ABSA Model

The Hugging Face Trainer class then simplifies the fine-tuning process by managing model training evaluation and saving the fine-tuned model. The approach then uses the saved fine-tuned model to extract implicit aspects. Following the fine-tuned process, the model extracts implicit aspects from the remaining training dataset comprising 1,859 data. We analyze each review text to detect aspects using a predefined dictionary of implicit aspects and their synonyms, as shown in Figure 3.

```
SYNONYMS = {
    "Product Effectiveness": ["remove", "works well", "refreshing", "prevents", "helps", "removes makeup", "cleansing"],
    "Skin Sensitivity": ["sensitive", "doesn't irritate", "gentle on skin", "non-irritating", "for sensitive skin", "mild"],
    "Skin Comfort": ["soft", "smooth", "comfort", "feels nice", "soothing", "hydrated", "non-greasy"],
    "Scent": ["smell", "scent", "fragrance", "odor", "perfume", "aroma", "fresh"],
    "Convenience": ["easy to use", "convenient", "handy", "great for travel", "portable", "simple to apply"],
    "Product Quality": ["quality", "well-made", "reliable", "durable"],
    "Product Longevity": ["lasts long", "long-lasting", "goes a long way","last for a long time"],
    "Price": ["affordable", "cheap", "expensive", "value", "cost", "price"],
    "Packaging": ["packaging", "container", "box", "sealed", "bottle", "wrapper"],
    "Delivery Speed": ["fast delivery", "quick delivery", "on-time", "prompt", "speed"],
    "Product Texture": ["texture", "thick", "thin", "consistency"],
    "Hydration Effect": ["hydrates", "keeps skin moist", "retains moisture"],
    "Flavor/Taste": ["flavor", "taste", "delicious", "yummy", "savory", "sweet"],
    "Fabric Safety": ["safe for fabric", "gentle on clothes", "no bleach stains", "fabric-friendly", "soft"],
    "Cleaning Effectiveness": ["cleans well", "cleans", "effective cleaner", "removes stains", "deep cleaning"],
    "Nutritional Value": ["nutritional", "healthy", "low calorie", "low sugar", "gluten-free"],
    "Product Size": ["portion", "serving", "quantity", "big", "small"],
    "Moisturizing Effect": ["moisturizing", "softening", "nourishing"],
    "Residue": ["no residue", "leaves residue", "build-up"]
}
```

Figure 3: Synonyms for Implicit Aspects

Identifying implicit aspects involves analyzing sentences by comparing words to a predefined list of aspects and synonyms. The method ensures case consistency and checks for matches. The model detects and records each aspect, then continues the process until it captures all relevant aspects. Indirect expressions through related terms often reveal implicit aspects. For example, users may describe 'Skin Comfort' using terms like 'soft', 'smooth', or 'soothing'. Defining these synonyms helps the model capture different expressions of the same aspect, improving accuracy in implicit ABSA. Once the model identifies a related term, it extracts the corresponding aspect.

After identifying implicit aspects, the model extracts contextual snippets or implicit terms, specifically five words before and after each aspect, to retain meaningful information. The fine-tuned BERT model then processes the tokenized text and predicts sentiment by assigning a score based on positive, negative, or neutral classifications. It stores the processed data in a new dataset that includes essential fields such as 'review_id', 'sentence', 'aspect', 'implicit terms', 'sentiment', and 'category', as illustrated in Figure 4. This dataset subsequently supports the rule-based detection phase in identifying fake reviews.

review_id	sentence	aspect	implicit_terms	sentiment	sentiment_score	category
0	Shop bought is much more expensive than I paid for these, unless a special offer is on so this deal was excellent value for money. Full of flavour tasty snack anytime. Definitely recommend	Price	shop bought is much more expensive than I paid for these	Positive	0.981838	Foods
1	i'm not sure it lives up to all the hype that Comfort is clearly a leading brand in the market leader and if you want to use fabric softer inspires confidence. We personally only use fabric softener and on towels but this certainly did seem to lead them very soft and was a nice fragrance . Value for money this is an excellent product definitely better and cheaper brands some of which just don't work or smell very harsh .	Skin Comfort	seem to lead them very soft	Positive	0.990571	Homecare
1	i'm not sure it lives up to all the hype that Comfort is clearly a leading brand in the market leader and if you want to use fabric softer inspires confidence. We personally only use fabric softener and on towels but this certainly did seem to lead them very soft and was a nice fragrance . Value for money this is an excellent product definitely better and cheaper brands some of which just don't work or smell very harsh .	Scent	don ' t work or smell very harsh .	Negative	-0.587351	Homecare
1	i'm not sure it lives up to all the hype that Comfort is clearly a leading brand in the market leader and if you want to use fabric softer inspires confidence. We personally only use fabric softener and on towels but	Price	value for money	Positive	0.990946	Homecare

Figure 4: Example of the New Formatted Dataset with Implicit ABSA

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3.3.2 Fake review detection through indicators of fake reviews

This step detects fake reviews by evaluating exaggerated sentiment, lack of specificity, and repetitive wording (duplicated reviews), all of which serve as key indicators of fake reviews. The approach determines these indicators by analyzing sentiment scores from the implicit ABSA model and computing both word counts and similarity scores (based on cosine similarity) for implicit terms. It then groups the results by 'review_id' and calculates average indicator values to assess the likelihood of a fake review. Figure 5 illustrates the flowchart for the fake review detection process.

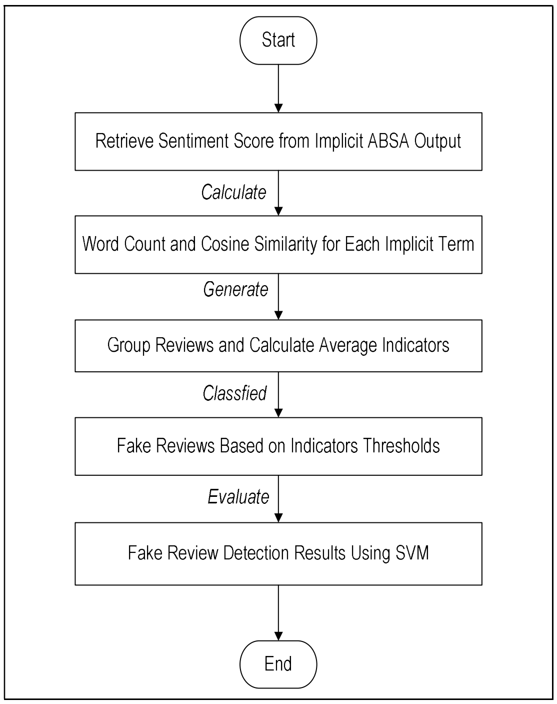

Figure 5: Flowchart for Fake Review Detection

To calculate word count and cosine similarity based on individual implicit terms, the approach first computes the aspect word count for each review by counting the number of words in the 'implicit_terms' column, as illustrated in Figure 6. Short implicit terms may indicate fake reviews, making this count a valuable indicator. Then, we stored the computed values in a new column labelled 'aspect_word_count' for further analysis.

review_id	implicit_terms	aspect_word_count	lack_of_specificity
0	shop bought is much more expensive than I paid...	11	No
1	seem to lead them very soft and was a nice fra...	11	No
1	don't work or smell very harsh .	7	No
1	was a nice fragrance . value for money this is an	11	No
2	they do the job . removes make up really well and	11	No
2	big which is brilliant great smell and they do...	11	No
5	it's decent fabric softener with a nice fragra...	9	No
5	fabric softener with a nice fragrance .	7	No

Figure 6: Example of Aspect Word Count Calculation

After calculating the aspect word count, the system computes the cosine similarity of implicit terms using TF-IDF vectorization to convert text into numerical vectors. It then applies a similarity threshold 0.5 to identify duplicate or highly similar reviews. The approach records the count of similar reviews in the 'duplicated_review' column, flagging any review with more than zero similar entries as duplicates, as illustrated in Figure 7.

review_id	implicit_terms	similar_review_count	duplicated_review
0	shop bought is much more expensive than I paid...	0	No
1	seem to lead them very soft and was a nice fra...	0	No
1	don't work or smell very harsh .	0	No
1	was a nice fragrance . value for money this is an	3	Yes
2	they do the job . removes make up really well and	3	Yes
2	big which is brilliant great smell and they do...	1	Yes
5	it's decent fabric softener with a nice fragra...	1	Yes
5	fabric softener with a nice fragrance .	1	Yes
7	but that ' s personal taste . sold mine on .	4	Yes

Figure 7: Example of Cosine Similarity Calculation

After calculating sentiment scores, aspect word count, and cosine similarity, the system uses these features to identify patterns indicative of fake reviews. However, relying solely on implicit terms based on individual may overlook broader contextual cues. To enhance detection, the approach groups reviews by 'review_id' and aggregates the indicators to evaluate fake reviews comprehensively.

The approach averages key indicators, which are sentiment score, aspect word count, and similar review count, for each review to enable a more accurate assessment. It then applies predefined thresholds, as detailed in Table 1, which show sentiment scores outside the range of -0.2 to 0.8, aspect word counts below 6, and similar review counts above 0 are suspicious. The approach classifies a review as fake only if it satisfies all three criteria, ensuring a systematic and reliable detection process.

Table 1: Key Indicators for Identifying Fake Reviews.

Indicator	Description	Indicator Value	Indicator Criteria
Sentiment scores	Extreme values may indicate exaggerated sentiments.	High sentiment scores (more than 0.8 or less than -0.2)	Exaggerated sentiment
Aspect word count	Low aspect word count suggests vagueness and lack of detail	Low aspect word count (less than 6 words)	Lack of specificity
Similar review count	High similarity suggests duplication or repetitive wording	More than 0 similar reviews (computed using cosine similarity)	Repetitive wording or Duplicated review

The approach classifies grouped reviews based on aggregated indicators, including average sentiment score, aspect word count, and similar review count. It labels a review as fake if we meet all specified conditions. Otherwise, it classifies the review as genuine. For example, Figure 8 illustrates that the approach flags 'review_id' 30 and 34 as fake due to exaggerated sentiment, low aspect word count, and high similarity, while it retains 'review_id' 36 as genuine despite some duplicated content.

review_id	fake_review	sentiment_score_avg	exaggerated_sentiment	aspect_word_count_avg	few_aspect_words	similar_review_count_avg	many_similar_reviews	Classification
21	0	0.9874442	yes	11	no	1	yes	Genuine
22	0	0	no	0	no	0	no	Genuine
23	0	-0.80822	yes	7	no	1	yes	Genuine
24	0	0	no	0	no	0	no	Genuine
25	0	0	no	0	no	0	no	Genuine
26	0	0.990407	yes	11	no	0	no	Genuine
27	0	0.9902058	yes	8.5	no	1	yes	Genuine
28	0	0.990876	yes	7	no	1	yes	Genuine
29	0	0.7244394	no	11	no	1	yes	Genuine
30	1	0.9814622	yes	4	yes	1	yes	Fake
31	0	0.6600376	no	7.333333333	no	0	no	Genuine
32	0	0	no	0	no	0	no	Genuine
33	0	0.9826219	yes	9.5	no	1	yes	Genuine
34	1	0.9907733	yes	5	yes	1	yes	Fake
35	0	0	no	0	no	0	no	Genuine
36	0	0.3473431	no	11	no	1	yes	Genuine
37	0	0	no	0	no	0	no	Genuine
38	0	0.6602803	no	7.333333333	no	0.666666667	yes	Genuine

Figure 8: Example of the Classification of Fake Reviews for Grouped Reviews

3.3.3 Imbalanced dataset handling

After classifying the reviews, the approach applies SMOTE to handle imbalanced data by generating synthetic samples for the minority class (fake reviews). This ensures a balanced dataset, improving the approach's ability to detect both fake and genuine reviews more effectively. Figure 9 illustrates the simplified flowchart for this process.

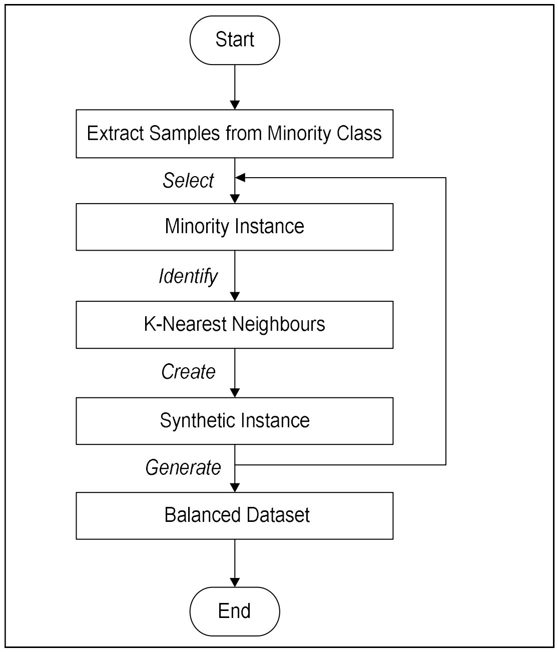

Figure 9: Simplified Flowchart of SMOTE Algorithm

SMOTE balances the dataset by generating synthetic samples through interpolation between nearest neighbors. The approach feeds the resulting balanced dataset into the SVM model, improving performance evaluation.

3.4 Evaluation

This phase is the final step in the development of the hybrid approach. It focuses on evaluating the performance metrics of the hybrid approach and the performance of the hybrid approach with different feature approaches. The assessment used accuracy, precision, recall, and F1 scores. We applied *k*-fold cross-validation with SVM to improve reliability and maintain a balanced class distribution.

Following prior research by Nti et al. [54], they used $k = 5$ and $k = 10$ for *k*-fold cross-validation because they are commonly used to balance bias and variance. At the same time, the study also considers k=7 to analyze its impact on the performance of the SVM model. This study specifically explores $k = 5$, $k = 7$, and $k = 10$, as they fall within the commonly used range of $k = 5$ to $k = 10$, ensuring a balance between efficiency, accuracy, and generalization without excessive computational cost. In each iteration, the approach trains the SVM on k–1 folds and validates it on the remaining fold, then averages the performance metrics across all folds to ensure a robust evaluation.

4. RESULTS AND DISCUSSION

4.1 Results of Implicit Aspect Extraction and Sentiment Analysis

4.1.1 Result of fine-tuned model

The BERT-based model was fine-tuned on a small labelled dataset (207 samples, 10% of the training set) to extract implicit aspects and perform SA. The model demonstrated effective learning within three epochs, as training beyond this point led to overfitting, reflected by an increase in validation loss. Thus, the model selects three epochs as the ideal training duration to optimize generalization and maintain efficient learning.

4.1.2 Distribution of implicit aspects across categories

The extracted implicit aspects varied across four product categories: personal care, home care, foods and refreshments. The findings reveal that sensory attributes such as "Scent" and "Flavour/Taste" were the most frequently mentioned aspects, particularly in personal care and food products, highlighting their strong influence on consumer satisfaction. Meanwhile, affordability, particularly "Price", played a secondary but significant role, especially for home care and refreshments, where cost-conscious purchasing decisions are common.

Beyond sensory and affordability aspects, functional attributes like "Product Effectiveness" and "Packaging" were particularly relevant in home care products, where usability and efficiency are key considerations. While scent and taste dominated personal care and food categories, affordability and product functionality were more critical in refreshments and home care. These insights indicate that consumer preferences vary across categories, emphasizing the need for businesses to tailor their products based on these key factors.

4.1.3 Distribution of sentiment analysis by implicit aspects

The sentiment distribution across implicit aspects provides insights into consumer perceptions and product satisfaction. Positive sentiments were dominant, particularly for aspects such as "Scent", "Price", and "Skin Comfort", reflecting strong consumer satisfaction in personal care and home care products. These findings suggest that consumers appreciate pleasant fragrances, affordability, and comfort-related benefits, which are critical factors in purchasing decisions.

On the other hand, users primarily associate negative sentiments with "Product Effectiveness", "Price", and "Packaging", highlighting concerns about unmet expectations, affordability, and durability. Consumers often expressed dissatisfaction when a product failed to deliver its promised benefits, considered it too expensive, or had packaging issues affecting usability. Neutral sentiments were minimal, suggesting consumers tend to express clear positive or negative opinions on key product attributes rather than remain indifferent. These results reinforce the importance of improving product functionality, pricing strategies, and packaging designs to enhance customer satisfaction.

4.2 Results of Fake Review Detection

4.2.1 Classification of fake reviews

This section presents fake review detection results using implicit ABSA and rule-based indicators. The process begins with individual-level analysis, where the approach breaks down reviews into implicit aspects, sentiment score, aspect word count, and similar review count. At the grouped level, the approach aggregates these indicators and uses their combined influence to determine whether a review is fake or genuine.

The approach extracts implicit aspects at the individual level but does not yet apply classification, as illustrated in Table 2. It analyses each aspect separately and records the sentiment score, aspect word count, and similar review count. For example, Review ID 269 contains the aspects 'Scent' ('*Smells good*') and 'Price' ('*Not expensive*'), both with a sentiment score of 0.99, an aspect word count of 2, and a similar review count of 4.

Building on this, Table 3 presents the grouped classification, where the approach averages indicators across all implicit aspects within each review. It classifies a review as fake if it exhibits exaggerated sentiment (high sentiment score), lacks specificity (low aspect word count), and shows repetitive wording (high similar review count). Based on these criteria, the system classifies Review Id 269 as fake, as it meets all conditions.

Table 2: Example of Reviews on Individual-level Analysis Before Classification

Review Id	Full Review Text	Implicit Terms	Implicit Aspects	Key Indicators of Fake Review		
				Sentiment Scores	Aspect Word Count	Similar Review Count
2	I am so glad I tried These wipes I've been searching for the right ones for months. These micellar wipes are really big which is brilliant great smell and they do the job. Removes make up really well and is just amazing. I will definitely be buying these again	Big which is brilliant	Product Size	0.89	4	0
		Great smell	Scent	0.88	2	1
		They do the job. Removes make up really well	Product Effectiveness	0.99	10	0
71	I bought 2 of the same bottles and they were both different colour and had a different fragrance.	bought 2 of the same bottles and they were both different colour	Packaging	0.91	12	1
		had a different fragrance.	Scent	0.98	5	1
105	I'm such a fan of gel creams and this one is fantastic. Very smooth application and really hydrating. You wake up with the smoothest skin in the morning. Great new addition to my night time skin routine and very reasonably priced!	Very smooth application and really hydrating.	Skin Comfort	0.99	11	0
		Skin routine and very reasonably priced!	Price	0.87	7	0
136	Love this cream. It heavy but not overly so, soaks into your skin and keeps you moisturized for ages. Has a really soft fragrance but not overly perfumed, reminded me of my holiday. I suffer with really dry arms and hands and after a few applications looked and felt significantly better.	soaks into your skin and keeps you moisturized for ages.	Skin Comfort	0.98	11	1
		has a really soft fragrance but not overly perfumed	Scent	0.87	9	1
		looked and felt significantly better.	Product Effectiveness	0.86	5	0
222	Great product! Great price	Great product! Great Price	Price	0.99	5	23
261	I love the refreshing scent of this cream, it is a light consistency which isn't to heavy on the skin and sinks in well. It would be to have a little bit more of a lasting moisturizing effect, but it does the job for the majority of the day.	I love the refreshing scent of this cream,	Scent	0.99	9	6
		it is a light consistency which isn't to heavy on the skin	Product Texture	0.98	12	1
		It would be to have a little bit more of a lasting moisturizing effect,	Moisturizing Effect	0.92	15	1
		it does the job for the majority of the day.	Product Effectiveness	0.99	10	4
269	smells good and not expensive	Smells good	Scent	0.99	2	4
		not expensive	Price	0.99	2	4
728	Great buy, smells gorgeous	Great buy	Price	0.98	2	5
		Smells gorgeous	Scent	0.97	2	3
1111	Nice and cost effective	Nice and cost effective	Price	0.99	4	2
1512	Thick and creamy smelt fresh	Thick and creamy	Product Texture	0.89	3	1
		smelt fresh	Scent	0.98	2	1

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Table 3: Example Result of Fake and Genuine Reviews Based on Grouped Classification

Review Id	Full Review Text	Implicit Aspects	Key Indicators of Fake Review			Result
			Sentiment Score Average (> 0.8 or < -0.2)	Aspect Word Count Average (< 6)	Similar Review Count Average (> 0)	
2	I am so glad I tried These wipes I've been searching for the right ones for months. These micellar wipes are really big which is brilliant great smell and they do the job. Removes make up really well and is just amazing. I will definitely be buying these again	Product Effectiveness, Scent, Product Size	0.66	5.3	0.3	Genuine
71	I bought 2 of the same bottles and they were both different colour and had a different fragrance.	Scent, Packaging	0.95	9.0	1.0	Genuine
105	I'm such a fan of gel creams and this one is fantastic. Very smooth application and really hydrating. You wake up with the smoothest skin in the morning. Great new addition to my night time skin routine and very reasonably priced!	Skin Comfort, Price	0.93	9.0	0.0	Genuine
136	Love this cream. It heavy but not overly so, soaks into your skin and keeps you moisturized for ages. Has a really soft fragrance but not overly perfumed, reminded me of my holiday. I suffer with really dry arms and hands and after a few applications looked and felt significantly better.	Skin Comfort, Scent, Product Effectiveness	0.91	8.3	0.7	Genuine
222	Great product! Great price	Price	0.99	5.0	23.0	Fake
261	I love the refreshing scent of this cream, it is a light consistency which isn't to heavy on the skin and sinks in well. It would be to have a little bit more of a lasting moisturizing effect, but it does the job for the majority of the day.	Product Effectiveness, Scent, Product Texture, Moisturizing Effect	0.97	11.5	3.0	Genuine
269	smells good and not expensive	Scent, Price	0.99	2.0	4.0	Fake
728	Great buy, smells gorgeous	Scent	0.98	2.0	4.0	Fake
1111	Nice and cost effective	Price	0.99	4.0	2.0	Fake
1512	Thick and creamy smelt fresh	Scent, Product Texture	0.94	2.5	1.0	Fake

4.2.2 Indicators of values between fake and genuine reviews

Figure 10 illustrates the average values of three key indicators, which are sentiment score, similar review count (cosine similarity flags), and aspect word count, to differentiate between fake and genuine reviews. This visualization highlights distinct patterns in fake reviews, validating the effectiveness of these indicators.

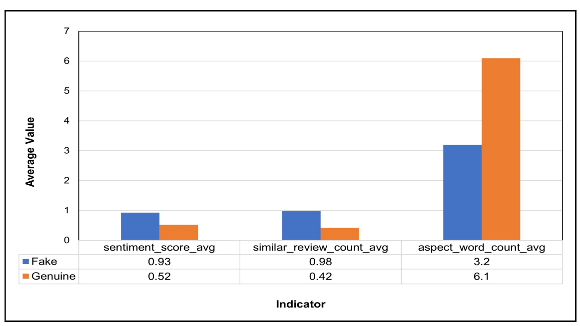

Figure 10: Average Indicator Values for Fake and Genuine Reviews

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The results show that fake reviews have higher sentiment scores (0.93 vs. 0.52), reflecting exaggerated language intended to manipulate perceptions. They also exhibit greater similarity to other reviews (0.98 vs. 0.42), indicating repetitive or templated content. Additionally, genuine reviews are more detailed, with an average aspect word count of 6.10, while fake reviews (3.20) lack specificity, often using vague or generic language. These findings confirm that genuine reviews are more original and detailed, whereas fake reviews rely on exaggerated sentiment and repetitive patterns.

4.2.3 Distribution of fake reviews across categories

Figure 11 illustrates the distribution of fake reviews across product categories, with home care having the highest count (66 fake reviews). This may be due to high competition and consumer expectations in the cleaning products market, leading to manipulative reviews to boost product reputation. Personal care follows with 32 fake reviews, likely driven by consumer sensitivity to product quality and health effects, prompting aggressive marketing tactics.

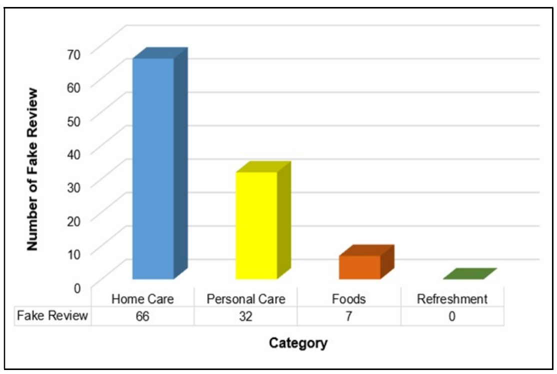

Figure 11: Distribution of Fake Reviews by Product Categories

In contrast, foods have fewer fake reviews (7). This is possibly due to frequent real consumer feedback and a lower incentive for manipulation in short-term consumables. The approach identified no fake reviews in the refreshments category, likely because these low-cost and straightforward products depend less on online reviews.

4.2.4 Correlation matrix analysis between indicators and classification of fake reviews

Figure 12 presents the correlation matrix between fake review indicators and fake review classification. The results show a weak positive correlation (0.20) between sentiment score and fake reviews, indicating that exaggerated sentiment has a minor influence on detection. Similarly, aspect word count has a weak negative correlation (-0.15) with fake reviews, suggesting that shorter reviews are slightly more likely to be fake.

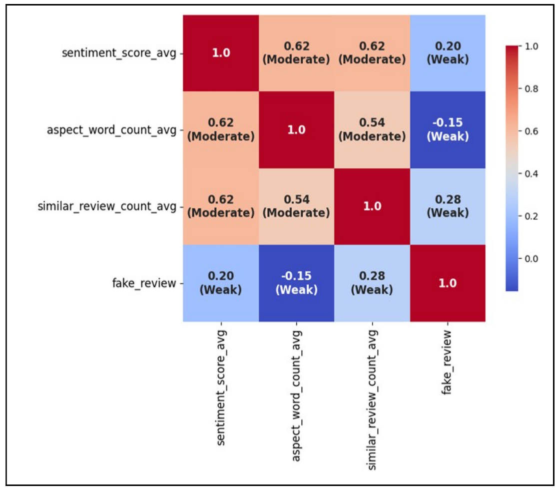

Figure 12: Correlation Matrix of Indicators and Classification of Fake Reviews

The similar review count shows a higher positive correlation (0.28) with fake reviews, making repetitive wording a more reliable indicator than sentiment score or word count. Additionally, moderate correlations exist between indicators, such as sentiment score and aspect word count (0.62), reflecting their interconnected nature. These findings highlight that no single indicator is sufficient for accurate fake review detection, reinforcing the need for a multi-indicator approach.

4.3 Results of Imbalanced Dataset Handling

4.3.1 Class distribution changes before and after SMOTE

The approach applied the SMOTE technique to balance the class distribution between genuine and fake reviews. Figure 13 shows that the fake class had only 107 samples before SMOTE. This creates a severe imbalance that hinders accurate classification. After SMOTE, the fake class was oversampled to 1751 samples, matching the genuine class and ensuring equal representation during training. This improves the approach's ability to classify underrepresented instances.

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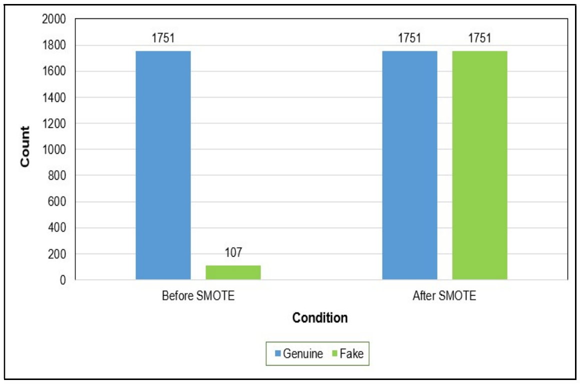

Figure 13: Distribution of Fake and Genuine Class Before and After SMOTE

4.3.2 Performance metrics before and after SMOTE

Table 4 presents stratified *k*-fold cross-validation results before and after applying SMOTE. Before SMOTE, the approach achieved high accuracy (~0.99) and perfect precision (1.00), indicating strong confidence in predicting positive instances. However, recall values varied (0.53 to 0.90), showing difficulty in detecting all fake reviews, leading to false negatives. $K = 5$ provided the best balance between accuracy (0.99) and recall (0.78), while $k = 10$ showed greater recall fluctuations (0.55 to 0.90), making it less stable for detecting the minority class.

As for after SMOTE, recall improved significantly (~0.90 to 1.00), enhancing the detection of minority class instances. However, precision decreased (~0.46 to 0.83) due to an expected increase in false positives when balancing the dataset. Despite this, the F1 score remained stable (~0.74 to 0.95), ensuring a better balance between precision and recall. Overall, SMOTE improved recall while maintaining high accuracy (~0.95 to 0.99), a necessary trade-off for trust management and fake review detection, where identifying potential threats outweighs perfect precision.

Table 4: Results of k-fold Cross-validation Before and After SMOTE

k	**Before SMOTE**					**After SMOTE**				
	Fold	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**Fold**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
5	1	0.99	1.00	0.81	0.89	1	0.96	0.61	0.95	0.74
	2	0.99	1.00	0.76	0.86	2	0.97	0.69	0.95	0.80
	3	0.99	1.00	0.86	0.92	3	0.94	0.50	0.95	0.66
	4	0.99	1.00	0.81	0.89	4	0.97	0.67	0.95	0.78
	5	0.98	1.00	0.67	0.80	5	0.94	0.49	0.95	0.65
	Average	**0.99**	**1.00**	**0.78**	**0.88**	**Average**	**0.96**	**0.59**	**0.95**	**0.73**
7	1	0.98	1.00	0.73	0.85	1	0.96	0.64	0.93	0.76
	2	0.99	1.00	0.80	0.89	2	0.95	0.52	0.93	0.67
	3	0.99	1.00	0.87	0.93	3	0.99	0.83	1.00	0.91
	4	0.99	1.00	0.80	0.89	4	0.94	0.48	0.93	0.64
	5	0.99	1.00	0.87	0.93	5	0.97	0.65	1.00	0.79
	6	0.99	1.00	0.87	0.93	6	0.95	0.56	0.93	0.70
	7	0.97	1.00	0.53	0.70	7	0.93	0.47	0.93	0.62
	Average	**0.99**	**1.00**	**0.78**	**0.87**	**Average**	**0.96**	**0.59**	**0.95**	**0.72**
10	1	0.99	1.00	0.82	0.90	1	0.97	0.65	1.00	0.79
	2	0.98	1.00	0.73	0.84	2	0.94	0.50	0.82	0.62
	3	0.98	1.00	0.73	0.84	3	0.93	0.46	1.00	0.63
	4	0.99	1.00	0.90	0.95	4	1.00	1.00	1.00	1.00
	5	0.99	1.00	0.90	0.89	5	0.94	0.50	1.00	0.67
	6	0.99	1.00	0.80	0.95	6	0.94	0.50	0.90	0.64
	7	0.99	1.00	0.90	0.89	7	0.97	0.62	1.00	0.77
	8	0.99	1.00	0.80	0.78	8	0.97	0.69	0.90	0.78
	9	0.99	1.00	0.73	0.84	9	0.93	0.48	1.00	0.65
	10	0.97	1.00	0.55	0.71	10	0.95	0.56	0.91	0.69
	Average	**0.99**	**1.00**	**0.78**	**0.88**	**Average**	**0.95**	**0.60**	**0.95**	**0.72**

Table 5 compares performance metrics before and after SMOTE, highlighting the best-performing k-fold cross-validation for each case. Before SMOTE, the best performance was at $k = 5$, and the approach achieved 99% accuracy and 100% precision but with lower recall (78%), indicating difficulty in detecting the minority class. This imbalance manifests in the F1 score (88%), which considers both precision and recall. After SMOTE, the best k-fold cross-validation was at $k = 5$, with recall improving to 95%, ensuring better detection of fake reviews in an imbalanced dataset. However, this came at the cost of precision dropping from 100% to 59%, increasing false positives. As a result, the F1 score declined to 73%, reflecting the trade-off between recall and precision. Despite a slight drop in accuracy (99% to 96%), the hybrid approach effectively improves minority class detection while maintaining strong overall performance.

Table 5: Results of Performance Metrics Before and After SMOTE

Condition	k	Fold	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Before SMOTE	5	Average	99	100	78	88
After SMOTE	5	Average	96	59	95	73

Figure 14 illustrates these changes, showing that before SMOTE (red line), the recall was low (78%), leading to many missed fake reviews. After SMOTE (green line), recall increased to 95%, prioritizing fake review detection despite a trade-off in precision. With accuracy still high at 96%, the hybrid approach balances recall and precision, ensuring better detection of fake reviews in imbalanced datasets.

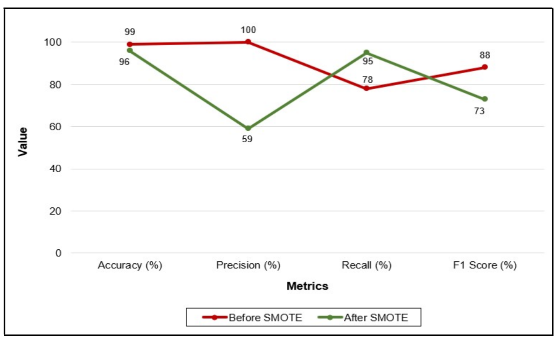

Figure 14: Comparison of Performance Metrics Before and After SMOTE

4.4 Evaluation

After analyzing each component of the hybrid approach, it evaluates the performance metrics and the performance of the hybrid approach with different feature approaches in fake review detection. This assessment determines the hybrid approach's effectiveness and showcases its ability to enhance fake review detection by integrating implicit ABSA and imbalanced dataset handling.

Then, we applied the stratified k-fold cross-validation exclusively to the training dataset to assess the hybrid approach's robustness and stability across multiple training and validation splits. This method prevents over-reliance on specific subsets and provides a reliable performance estimate during training. However, k-fold results cannot serve as final performance metrics, as the approach has already encountered this data during training. The final evaluation requires independent testing data to ensure the hybrid approach generalizes effectively to unseen real-world scenarios.

We evaluate the approach's performance on an independent testing dataset to assess the hybrid approach's generalization to unseen data. Table 6 shows the final metrics, which are 96% accuracy, 60% precision, 100% recall, and a 75% F1 score. The approach excels in recall, detecting all fake reviews, but the lower precision (60%) indicates false positives, where the approach misclassifies genuine reviews as fake. This recall-precision trade-off is common in imbalanced datasets. While k-fold cross-validation ensures training robustness, testing metrics provide an unbiased measure of real-world performance.

Table 6: Final Performance Metrics of the Hybrid Approach Based on Testing Dataset

Metrics	Final Performance (%)
Accuracy	96
Precision	60
Recall	100
F1 Score	75

Table 7 compares the hybrid approach's performance with different feature approaches on fake review detection. For consistency, we applied an SVM classifier across all approaches, which are 1) as a standalone SVM baseline, 2) combined with BERT and rule-based features, and 3) as part of the whole hybrid approach integrated with SMOTE.

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This setup enables a fair assessment of how each feature combination contributes to detection improvements, ultimately leading to the final effectiveness achieved by the hybrid approach.

Table 7: Comparison Performance of the Hybrid Approach with Different Feature Approaches on Fake Review Detection

Feature Approaches	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
SVM Baseline	95	54	50	52
BERT + Rule-based + SVM	97	95	46	63
BERT + Rule-based + SMOTE + SVM (This research)	96	60	100	75

The results in Figure 15, derived from Table 7, present a comparison between the SVM baseline, the BERT + Rule-based + SVM, and the constructed hybrid approach in this research (BERT + Rule-based + SMOTE + SVM). The SVM baseline model achieved an accuracy of 95%, a precision of 54%, a recall of 50%, and an F1 Score of 52%. These results indicate a relatively balanced but modest ability to detect fake reviews, with limited sensitivity reflected in the recall value.

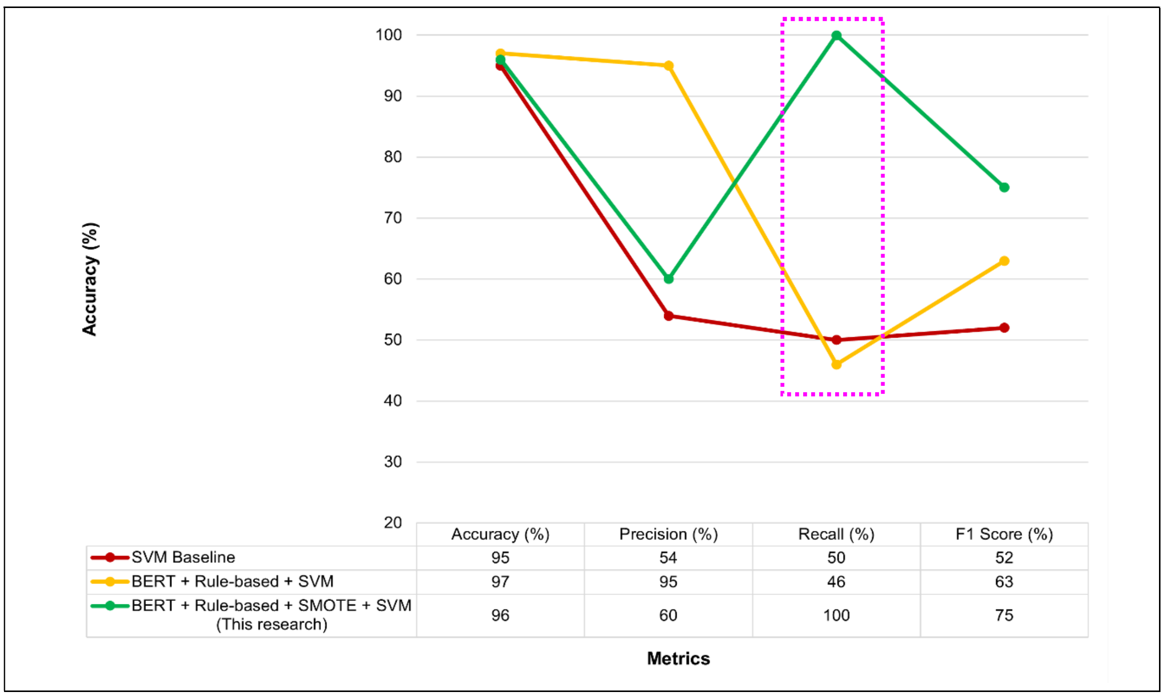

Figure 15: Comparison Performance of the Hybrid Approach with Previous Research Results

Meanwhile, the BERT + Rule-based + SVM approach showed marked improvements in accuracy (97%) and precision (95%), along with a higher F1 score of 63%. However, recall slightly declined to 46%, suggesting that while the approach effectively identified clearly defined patterns, it may have overlooked reviews lacking explicit rule-based cues.

In contrast, the hybrid approach (this research) demonstrated a more balanced performance by incorporating SMOTE to address class imbalance. It achieved 96% accuracy and a perfect recall of 100%, with an F1 score of 75%. Although precision dropped to 60%, the increase in recall is critical for fake review detection, where missing a deceptive review poses a greater risk than misclassifying a genuine one.

Overall, the comparison highlights the hybrid approach's robustness. While the other approaches emphasize precision, the constructed hybrid approach ensures comprehensive coverage of fake reviews by combining contextual signals

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from BERT, rule-based heuristics, and balanced data representation. This makes it a more effective and generalizable solution for real-world fake review detection tasks, particularly where high recall is a priority.

5. CONCLUSION AND FUTURE WORK

This study developed a hybrid approach integrating implicit ABSA and imbalanced dataset handling to enhance fake review detection. The approach combines BERT for implicit aspect extraction and SA, rule-based indicators for detecting fake reviews, SMOTE for balancing the dataset, and SVM with *k*-fold cross-validation to evaluate performance. During the *k*-fold cross-validation process, the approach initially achieved lower recall (78%) before applying SMOTE. After applying SMOTE, average performance improved, with recall increasing to 95%, showing the effectiveness of resampling in improving classification of the minority (fake review) class.

The final evaluation of the held-out testing dataset confirmed the hybrid approach's effectiveness, achieving 96% accuracy, 100% recall, 60% precision, and a 75% F1 score. These results demonstrate the approach's strong ability to detect all fake reviews while maintaining competitive overall performance. Although high recall ensures comprehensive fake review detection, the trade-off is moderate precision, indicating occasional misclassification of genuine reviews as fake, a common issue in imbalanced classification tasks.

However, this study presents a few challenges, including the time-consuming process of manually labelling implicit aspects and the recall-precision trade-off resulting from using SMOTE. Future research should aim to expand the labelled dataset to improve generalization and explore advanced resampling techniques such as Edited Nearest Neighbors (ENN) to enhance precision. This study contributes to the field by integrating implicit ABSA and imbalanced dataset handling into a hybrid approach, offering a more reliable and interpretable approach to fake review detection for both businesses and researchers.

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