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Optimisation of Sentiment Analysis for E-Commerce

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Abstract

Sentiment analysis is widely used today to make data-driven decisions in different industries, starting from marketing and including brand management, reputation monitoring, and customer satisfaction analysis. Its growing importance is closely linked with so-called 'word-of-mouth' communication, from reading online reviews to writing comments on social networks. Effective separation of sentiments ensures that companies' responses are timely and critical patterns are seen in big data sets. Statistical measures, information gain, correlation-based approaches, etc, have been employed for the feature selection. Still, the problem associated with text data mining is that they don't convey the text's relative difficulty and additional features. To fill this gap, our research proposes a new feature selection technique through Ant Colony Optimization (ACO) and K Nearest Neighbour (KNN) performed on 28,000 customer reviews in different product categories. The results, therefore, showed an overall accuracy of 80.1%, with the Support Vector Machine (SVM) set at 80.5% on each selected feature, which was slightly higher than the Convolutional Neural Network (CNN), which scored a 78.41% accuracy. SVM remains on the mark of 83%, and for CNN, the rate achieved on the same was 80.8% when both were applied to the entire dataset. These facts rejected the infallibility of the simple and complex algorithms used singly in the sentiment classification, indicating that more sophisticated algorithms like ACO and KNN can provide business solutions to improve their service delivery based on customers' feedback.

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1 Introduction

The digital revolution of the 21st century has dramatically changed the way we do business, reshaping how companies and customers interact. E-commerce has moved to the forefront of global trade, becoming more than just a platform to buy and sell—it's now an essential part of everyday life. Consumers today don't just shop; they embark on personalized journeys, exploring a vast range of products and services tailored to their preferences. E-commerce platforms provide more than just products—they offer convenience, customized experiences, and nearly limitless choices.

Customer feedback, whether it's in the form of product reviews, social media comments, or direct interactions, has become a goldmine of valuable insights [1–3]. Understanding these diverse and often complex sentiments is key to meeting customers' needs, preferences, and concerns. It's no longer just about what customers say—it's about understanding how they feel, which helps businesses improve their services, build long-term loyalty, and stay competitive.

But figuring out the market's collective mood in today's fast-paced digital world is no easy task. Businesses need to sift through vast amounts of data from multiple sources to transform raw text into meaningful insights. To truly understand what today's consumers want, companies need to go beyond standard algorithms—they need to get to the heart of what drives people's decisions. This means understanding not just the words but also the emotions and desires behind them.

This is where advanced techniques like swarm intelligence and nearest neighbour algorithms come into play. These methods help companies efficiently navigate the complexity of digital discourse, providing a deeper understanding of customer sentiments and leading to more insightful and empathetic decision-making.

Sentiment analysis, which is a vital part of Natural Language Processing (NLP), is now essential for making sense of the vast amounts of text data that businesses deal with. Traditionally, sentiment analysis relied on rule-based systems and machine learning algorithms to determine whether feedback was positive, negative, or neutral. But these approaches have often struggled with the nuances of human language—things like context, tone, and how people express themselves, especially in e-commerce, where feedback can vary greatly.

One major limitation of older methods is that they don't always handle the fluid nature of language well. For example, the same word can have different meanings depending on context. In e-commerce, this is particularly important—take the word "cheap," for instance. In one context, it might be seen as a positive, meaning affordable. But in another, it could suggest poor quality, leading to a negative perception [4]. These subtle shifts in meaning often cause lexicon-based approaches to misclassified feedback, which can blur the line between positive and negative sentiments.

Similarly, machine learning algorithms have their own set of challenges. These models require vast amounts of labelled data, which can be difficult and expensive to obtain, especially in the fast-moving world of e-commerce, where new products and trends emerge constantly [5–8]. Moreover, human language is full of ambiguities—sarcasm, irony, and cultural references are shared online, and they often trip up models trained on more structured datasets. This can lead to inaccurate interpretations of sentiment. To tackle these issues, we need a new approach that combines human language's flexibility with the precision of advanced computational techniques, like swarm intelligence and nearest neighbour algorithms.

1.1 Swarm Intelligence: Drawing Inspiration from Nature

The natural world has long inspired human creativity, leading to significant advancements in artificial intelligence. Amid the complexities of modern data processing, swarm intelligence shines as a promising approach, drawing on nature's collective wisdom. Inspired by the behaviour of social insects like ants and bees, swarm intelligence algorithms surpass traditional computing methods by leveraging the coordinated actions of individual units following simple rules. This collective intelligence mirrors the synergy in natural swarms, where each member contributes to the group's knowledge, creating a resilient, decentralized problem-solving method.

In e-commerce, characterized by diverse and nuanced customer feedback, swarm intelligence becomes a valuable tool. These algorithms can effectively navigate unstructured textual data, capturing the essence of customer sentiments with high precision. By mimicking the adaptive behaviors of natural swarms, swarm intelligence offers a new perspective on sentiment analysis, aligning more closely with the complex patterns of human expression.

In swarm intelligence, algorithms like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) have shown significant potential for nature-inspired problem-solving. ACO, inspired by ants' food-searching behavior, builds solutions based on pheromone trails, mimicking how ants communicate resource locations [9]. PSO, inspired by the social behavior of birds flocking or fish schooling, adjusts individual movements based on peers' experiences, effectively exploring solution landscapes [9]. These nature-derived algorithms exhibit remarkable adaptability and evolution, making them highly effective for sentiment analysis. As e-commerce platforms handle increasingly ambiguous and diverse data, swarm intelligence algorithms stand out as pioneering tools for deciphering complex customer sentiments.

1.2 Nearest Neighbours Algorithms: Proximity-Based Precision

Nearest neighbor algorithms, in particular the well-known k-nearest neighbors (KNN), have emerged as unsung heroes in the intricate tapestry of ML. This is especially true in pattern recognition and categorization [5]. KNN's ingenuity rests in its deceptively straightforward operation, which is based on the fundamental idea that things should be close together. KNN locates the data points that are most closely associated with an unlabeled instance among the huge available feature space. KNN can properly classify the instance by determining the classes of these nearby data points. This allows it to encapsulate sophisticated patterns that are frequently unreachable using traditional methods. This strategy is especially beneficial in the ever-changing environment of e-commerce, where client feelings are subtle, varied, and reliant on the context in which they are expressed. KNN allows for a deeper understanding of the subtle variations in customer emotions by adopting a granular approach to sentiment analysis. This ensures a level of accuracy that is indispensable for businesses that are attempting to comprehend the complexities of their customers' preferences and opinions.

KNN serves as a guiding light in the murky waters of the online e-commerce marketplace, where each click, view, and review is a part of a larger whole. E-commerce platforms can better understand customer feelings thanks to KNN's ability to recognize even the smallest similarities and differences among data points. KNN is a reliable tool for determining the preferences of a fashion-savvy client browsing various collections or understanding the precise needs of a tech-savvy customer searching for the perfect gadget. By deciphering the intricate web of customer interactions and sentiments, KNN enhances businesses' understanding of their clientele and enables them to tailor products and services to meet the diverse and ever-evolving market needs [10]. This makes KNN a cornerstone in the arsenal of tools used to navigate the complexities of the digital marketplace.

1.3 The Synergy: Integrating Swarm Intelligence and Nearest Neighbors

The combination of swarm intelligence and nearest-neighbor algorithms offers an innovative solution to the complexities of sentiment analysis in e-commerce. This fusion leverages the collective intelligence of swarm systems and the precision of nearest-neighbor algorithms, creating a synergy that surpasses traditional methods. Swarm intelligence, known for navigating vast solution spaces and finding optimal paths, enhances the analysis of customer attitudes by capturing diverse expressions and deciphering subtle, context-specific meanings in textual data. This detailed insight, paired with the accuracy of nearest-neighbor algorithms, forms a hybrid approach that promises to revolutionize how businesses understand and respond to customer sentiments in the dynamic world of e-commerce.

Swarm intelligence is the guiding intuition, navigating the complex maze of linguistic intricacies, while nearest neighbor algorithms provide precision, accurately classifying nuanced sentiments. This symbiotic relationship leverages the adaptability of swarm intelligence and the localized accuracy of nearest-neighbor algorithms, creating a dynamic balance capable of deciphering sentiments in real-time despite evolving linguistic trends and cultural references. This convergence enhances businesses' analytical capabilities and their ability to connect with customers on a deeper emotional level, transforming sentiment analysis. Computational approaches become empathic interpreters of human emotions, paving the way for a more meaningful and customer-focused e-commerce experience.

The remainder of this paper is organized as follows: **Section 2** delves into the theoretical foundations and literature of nearest neighbor algorithms and swarm intelligence. **Section 3** details the proposed framework detailing the integration process and experimental setup for sentiment analysis. **Section 4** provides results and discussion present and interpret the findings from the case studies of various experiments. **Section 5** analyzes the research implications for the e-commerce industry, highlighting the transformative potential of the hybrid approach and concludes the paper.

2 Related Work

Between 2018 and 2023, sentiment analysis in e-commerce saw a surge in research focused on optimizing methodologies through innovative approaches. Both academic researchers and industry professionals have dedicated significant effort to addressing the complex challenges of understanding customer sentiments in the dynamic e-commerce landscape. A highly discussed study [11] explored the use of PSO and KNN algorithms for analyzing customer sentiments in real-time e-commerce transactions. The research emphasized how PSO's adaptability enhances KNN by fine-tuning its parameters, improving sentiment classification accuracy and enabling quick adjustments to evolving language patterns in online interactions.

Building on this basis, the authors of [12] introduced a novel hybrid model that was inspired by the foraging behavior of ants (ACO) and the proximity-based precision of KNN. Their research focused on large-scale sentiment analysis in e-commerce forums, using swarm intelligence to dynamically adjust KNN's neighborhood size. This adaptive approach led to significant improvements in sentiment categorization, especially in scenarios where customer opinions changed rapidly.

Additionally, a study by [13] explored the combination of Swarm Intelligence, particularly the Bee Algorithm, with Nearest Neighbors algorithms for sentiment analysis in product recommendations. Their research enhanced sentiment accuracy and incorporated sentiment data into personalized product recommendations, thereby enriching the overall shopping experience for customers.

In a different approach, [14] examined sentiment-driven product recommendation algorithms for e-commerce platforms. They proposed a hybrid strategy integrating Swarm Intelligence algorithms for sentiment extraction and clustering with Nearest Neighbors algorithms for product similarity analysis. This combination improved sentiment analysis accuracy and enabled precise, personalized product recommendations based on individual customer sentiments, significantly influencing their purchasing decisions.

Research by [15] explored using swarm intelligence for sentiment analysis on Twitter, combined with lightweight discourse analysis methods. This approach effectively handles Twitter's brief messages' real-time and dynamic nature, leveraging swarm intelligence's decentralized adaptability to capture diverse perspectives and enhance sentiment understanding. Lightweight discourse analysis helps process short texts within Twitter's character limits. However, interpreting swarm intelligence outputs may require complex post-processing, and initial data quality can affect sentiment analysis effectiveness. Despite these challenges, the study demonstrates the potential of this approach for gaining rich, real-time insights from concise and rapidly changing social media content.

The research in [16] is considered a seminal work in sentiment analysis for its comprehensive exploration of various methods, ranging from traditional lexicon-based approaches to advanced machine learning and deep learning strategies. The book provides researchers and practitioners with a thorough understanding of these techniques, enabling informed decisions based on specific analytical needs. Liu's work [16] remains a valuable resource for those entering the complex domain of sentiment analysis.

Research by [17] underscores the importance of opinion mining and sentiment analysis in e-commerce customer reviews. The study emphasizes the need for accurate sentiment analysis to understand the complex nature of customer sentiments in the e-commerce sector. By focusing specifically on e-commerce, the research offers a detailed view of the unique challenges and opportunities in online customer feedback. It serves as a valuable guide for companies aiming to enhance customer experiences and adjust strategies based on feedback. However, its specialization may limit the generalizability of its findings to other industries. Additionally, the study's reliance on established methods may have overlooked innovative approaches, such as swarm intelligence and nearest neighbor algorithms, which could provide new insights. Despite these limitations, the research provides a strong foundation for understanding sentiment analysis challenges in e-commerce and offers practical insights for navigating online customer reviews.

The study [18] focuses on collaborative filtering methods, an essential aspect of personalized recommendation systems used in academic and e-commerce settings. It introduces collaborative topic modelling, which combines collaborative filtering with topic modelling to capture user preferences and content themes simultaneously. This approach enhances the system's ability to provide precise recommendations tailored to individual interests by identifying underlying topics in content. However, its effectiveness depends on the availability of high-quality, well-labeled data, which can be challenging and costly. Additionally, issues with interpretability and scalability may arise, particularly with large e-commerce databases. Despite these challenges, the study underscores the potential of collaborative topic modelling and the need to balance recommendation accuracy with the complexities of real-world data.

The survey by [19] provides a comprehensive overview of Recurrent Neural Networks (RNNs), exploring their structures, applications, and associated challenges. RNNs excel at recognizing sequential patterns, making them well-suited for sentiment analysis, which requires understanding context and data nuances. Their ability to process variable-length inputs and retain information from previous inputs allows them to interpret context more effectively than traditional feedforward networks. However, RNNs face significant issues, such as the vanishing gradient problem, which hampers their ability to learn long-term dependencies, and high computational costs that can lead to longer training times, especially with large datasets. Despite these limitations, the survey emphasizes the crucial role of RNNs in sentiment analysis for their capacity to decode complex sequential patterns in textual data.

The study in [20] explores sentiment analysis within e-commerce, focusing on the application of deep learning (DL) methods, particularly neural networks. One of the main advantages of DL algorithms is their ability to automatically learn complex patterns and representations from large volumes of unstructured text. With their layered architectures, Neural networks can effectively capture customer sentiments' intricate correlations and nuances, enhancing sentiment analysis models' accuracy. Additionally, DL models can adapt to evolving linguistic trends, making them resilient in the dynamic e-commerce environment. However, these benefits come with challenges, such as the need for substantial computational resources and large labeled datasets for effective training. Overfitting, where models excel on training data but struggle with new data, is also a concern if models are not properly calibrated. Despite these challenges, the research marks a significant advancement in improving the effectiveness and accuracy of sentiment analysis in e-commerce, laying the foundation for future developments in the field.

The review in [21] explores the potential of evolutionary computation approaches in sentiment analysis, highlighting the effectiveness of evolutionary algorithms for optimizing models. Inspired by natural evolution, these algorithms can adapt and evolve over generations to enhance performance and accuracy. Their versatility makes them well-suited for managing complex and dynamic datasets, especially in real-time applications and rapidly changing environments. Evolutionary algorithms can explore diverse solution spaces, offering comprehensive analyses. However, they require substantial computational resources and time, particularly with large datasets, and fine-tuning parameters and selecting optimal operators can be challenging. Despite these challenges, the review emphasizes the significant potential of evolutionary algorithms to improve the accuracy and effectiveness of sentiment analysis models, making them a valuable tool for nuanced e-commerce sentiment analysis.

The 2018 study by [22] explores transfer learning for sentiment analysis, focusing on label embedding techniques. Transfer learning leverages knowledge from one domain to enhance performance in another, particularly useful when labeled data is scarce. Label embedding techniques improve sentiment analysis models by providing a deeper understanding of sentiment structures, leading to better classification accuracy and generalization. However, selecting the right embedding methods can be challenging, as effectiveness depends on data characteristics and sentiment nuances. Additionally, implementing these models requires expertise in sentiment analysis and deep learning, complicating the deployment process. Despite these challenges, the study underscores the transformative potential of transfer learning and label embedding techniques, especially in resource-limited environments.

The research in [23] addresses the issue of class imbalance in machine learning for sentiment analysis, highlighting the advantages of ensemble learning approaches. Ensemble methods combine predictions from multiple models to enhance classification accuracy, making them practical for handling imbalanced sentiment distributions (positive, negative, or neutral). This approach helps ensure a more accurate representation of sentiment dynamics. However, challenges include increased computational cost, risk of overfitting, and the need for diverse base learners. Despite these difficulties, the study emphasizes the significant potential of ensemble methods to improve sentiment analysis models and address class imbalance issues.

The research paper [24] explores the integration of swarm intelligence with fuzzy classifiers, highlighting their combined benefits for sentiment analysis. Swarm intelligence, inspired by collective natural behavior, enhances fuzzy classifiers' adaptability and self-organization, which is crucial for the dynamic and subtle nature of e-commerce sentiment analysis. This synergy helps capture the nuances of human emotions in textual data. However, challenges include the complexity of integrating these systems and the impact of different swarm algorithms on performance. Despite these issues, the fusion of swarm intelligence and fuzzy classifiers offers a powerful framework for advancing sentiment analysis in e-commerce.

The study [25] on sentiment analysis in social networks explores the complexities of online interactions, revealing both benefits and challenges. It provides valuable insights into the nuances of sentiment expressed in digital conversations, which can help tailor marketing and customer engagement strategies on e-commerce platforms. However, the ambiguity of online language—affected by context, tone, and cultural differences—makes accurate sentiment interpretation difficult. Additionally, privacy and ethical concerns are significant issues in analyzing social media data. Despite these challenges, the study underscores its importance for improving sentiment analysis in the dynamic environment of social networks.

The review in [26] focuses on sentiment analysis in multilingual environments, with particular attention to Hindi, highlighting both challenges and solutions. The study reveals the nuances often overlooked by generic sentiment analysis models and offers tailored strategies for accurate sentiment interpretation in Hindi. This is valuable for organizations operating in linguistically diverse markets. However, the study's language-specific focus may limit its applicability to other languages and may not cover all regional dialects within Hindi, potentially missing some nuances. Despite these limitations, the research is a crucial resource for understanding and addressing the complexities of sentiment analysis in multilingual e-commerce, helping businesses develop culturally sensitive customer engagement strategies.

The study in [27] explores deep learning (DL) architectures for text interpretation [28], highlighting the ability of neural networks to understand and analyze textual data. One of the key strengths of this work is its emphasis on how DL models can automatically learn complex patterns and hierarchical representations from raw text, capturing nuanced sentiments that traditional methods might miss. The versatility of DL models makes them well-suited for handling diverse and dynamic e-commerce scenarios. However, challenges include the need for large amounts of labeled data, which can be difficult and costly to obtain, and issues with model interpretability. The complex nature of neural networks can make it hard to understand their decision-making processes, potentially affecting transparency in sentiment analysis.

The study in [29] examines sentiment analysis within Airbnb reviews, offering valuable insights that can be applied to analyzing sentiments on social media platforms. By focusing on a specific platform, the research provides a detailed understanding of sentiments within a niche community, revealing linguistic nuances and improving the accuracy of sentiment analysis. However, the context-specific nature of the findings may limit their applicability to other social media environments, and the study might not address all possible challenges. Despite these limitations, the research serves as a solid foundation for understanding and enhancing sentiment analysis on similar online platforms.

The groundbreaking study in [30] introduced Latent Dirichlet Allocation (LDA), a revolutionary topic modeling technique that transformed text analysis. LDA extracts hidden thematic structures from text, revealing underlying patterns without needing prior knowledge. This unsupervised approach makes LDA highly versatile, and suitable for various applications including sentiment analysis, where it enhances understanding by uncovering hidden themes. However, LDA has limitations, such as requiring a predefined number of topics and assuming documents are mixtures of topics, which can lead to inaccuracies in complex datasets. Despite these challenges, LDA remains a fundamental technique in natural language processing (NLP) and has significantly advanced sentiment analysis methods.

The research in [31] highlights significant advancements in text categorization and sentiment analysis through the integration of semantic features with Support Vector Machines (SVMs) and Word2Vec models. By incorporating semantic knowledge, these models achieve a deeper understanding of contextual meanings, enhancing their ability to capture nuanced emotions. This approach improves the accuracy of sentiment classification by better distinguishing between positive, negative, and neutral sentiments. However, it also introduces challenges, such as increased model complexity and computational demands, as well as variability in the quality of semantic representations. Despite these challenges, integrating semantic features into text classification represents a promising development, offering more precise and context-aware sentiment analysis, particularly valuable for e-commerce applications.

The research in [32] introduces a significant advancement in sentiment analysis through the creation of a continuously updated emotional lexicon. This lexicon adapts in real-time to evolving language and emotional complexities, making it highly relevant for analyzing contemporary data, especially in dynamic environments like social media and e-commerce. The main advantage is its ability to enhance sentiment analysis accuracy by providing a nuanced understanding of emotions. However, challenges include maintaining the lexicon's accuracy over time, as linguistic changes and cultural differences may require ongoing updates and resource investment. Despite these issues, the development of this dynamic emotional lexicon represents a major step forward in gaining deeper insights into customer emotions and preferences.

The survey in [33] offers a comprehensive overview of opinion mining and sentiment analysis, covering a broad range of tasks, methodologies, and applications. Its major strength lies in its thorough exploration of the field, providing valuable insights for both researchers and practitioners. This depth of coverage helps readers grasp the complexities of sentiment analysis in textual data. However, the broad scope might limit detailed discussions on emerging methodologies and trends. A more focused exploration of recent advancements could enhance the survey's utility, keeping readers informed about the latest developments in this rapidly evolving field.

Swarm Intelligence offers a decentralized approach to problem-solving, inspired by the synchronized behaviors of bees, ants, and other social organisms. These algorithms embody collective wisdom, adeptly navigating unstructured textual data with an intuitive and cooperative spirit found in nature. Swarm systems inherently manage ambiguity, diversity, and complexity—key attributes for understanding human emotions. Additionally, they explore broad problem-solving spaces and identify optimal pathways, providing the adaptability needed in the fast-evolving e-commerce environment.

Nearest Neighbors algorithms enhance the natural synergy of Swarm Intelligence with diligent proximity-based analysis. They identify patterns in customer expressions by examining the proximity of data points in feature space, capturing even subtle nuances. Their ability to recognize context-specific cues, such as linguistic nuances and cultural references, allows for a detailed understanding of emotions. This precision is crucial in the dynamic e-commerce landscape, where interactions between businesses and customers are constantly evolving.

These comprehensive strategies enable organizations to gain a deep, real-time understanding of customer emotions. Beyond recognizing positive, negative, or neutral expressions, they delve into the underlying feelings, motives, and preferences driving consumer behavior. The synergy between Swarm Intelligence and Nearest Neighbors algorithms surpasses conventional approaches, allowing businesses to not only respond to but also anticipate customer demands. This fosters genuine connections and enhances the online shopping experience. Incorporating these innovative ideas promises to transform e-commerce, ushering in an era where businesses truly understand and connect with their customers' needs.

3 Research Methodology

Understanding client emotions is crucial in the dynamic field of e-commerce. This study analyzes over 28,000 Amazon product reviews to uncover the complexities of customer feelings. It employs nature-inspired algorithms, such as ACO and KNN, for thorough feature selection. ACO's intelligent exploration and KNN's discriminating validation systematically identify the most relevant textual signals in product reviews. These selected features form the foundation for advanced sentiment analysis models, leveraging the accuracy of SVMs and the breadth of CNNs.

The combination of swarm intelligence and nearest neighbors algorithms optimizes sentiment analysis, revolutionizing how e-commerce platforms interpret customer feedback, tailor offerings, and enhance the overall customer experience, ultimately boosting satisfaction. This innovative approach embarks on a transformative journey into customer sentiment research, using a large dataset as the canvas and the synergy of intelligent algorithms as the tools. A detailed breakdown of the methodology is shown in Fig. 1.

3.1 Dataset Collection and Pre-processing

This study delves into customer sentiments using the "Amazon Products Consumer Reviews" dataset, which provides extensive insights from Amazon customer ratings across diverse product categories. These categories include Animal and Pet Supplies, Electronics, Furniture, Media, Health, Beauty, Office Supplies, Home & Garden, Toys, and Games. The varied product types create a rich tapestry of consumer attitudes, capturing the complexities of human emotions experienced in different aspects of daily life.

The dataset, a comprehensive compilation of over 28,000 customer reviews, was obtained from reliable sources, including the publicly accessible research repository at "https://data.world/datafiniti/consumer-reviews-of-amazon-products." Reviews are rated on a sophisticated scale from one to five stars, representing "very negative," "negative," "neutral," "positive," and

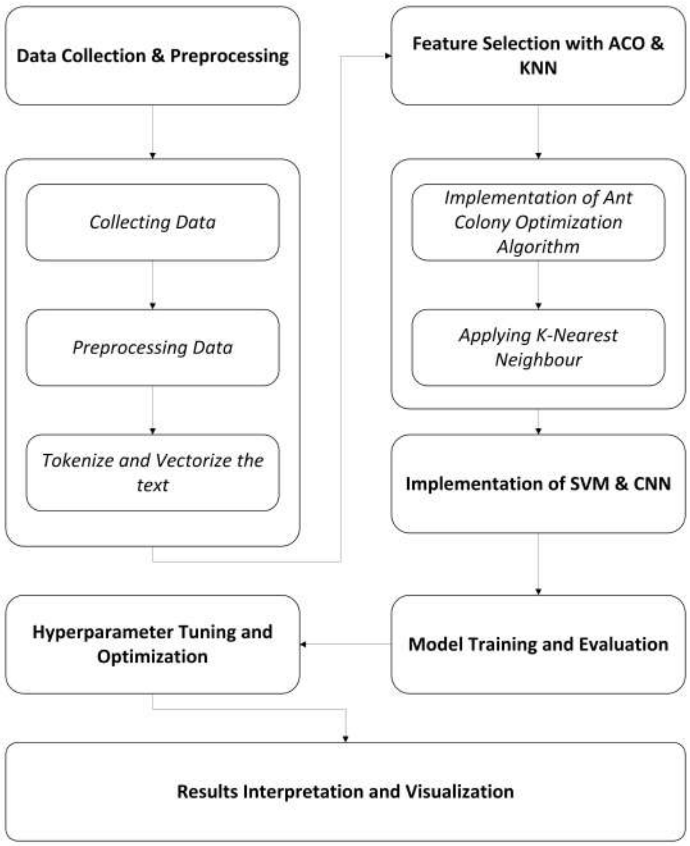

Figure 1. Framework of proposed research methodology

"extremely positive" sentiments. This dataset highlights an inherent class imbalance, adding complexity to sentiment analysis efforts.

In addition to the written reviews, the dataset includes extensive metadata that enriches the analysis. This metadata comprises product IDs, reviewer demographics (usernames and locations), review timestamps, and product ratings, providing essential context alongside emotive expressions. This supplemental information allows for a deeper exploration of customer sentiment, enabling researchers to understand not only the emotional tone of the reviews but also the demographic nuances and temporal trends influencing customer impressions.

In the preprocessing stage, the given dataset undergoes thorough cleaning and organization. This involves addressing missing data, standardizing date formats, and managing outliers. The 'reviews.text' column is particularly refined through tokenization, which breaks the text into individual words or phrases for detailed sentiment analysis. Lemmatization or stemming is then applied to reduce words to their base forms, ensuring consistency. Additionally, common issues like misspellings and abbreviations are corrected to enhance the quality of the textual data.

Categorical columns, such as brand and product categories, must be encoded into numerical values for compatibility with ML algorithms. Depending on the data, techniques like one-hot encoding or label encoding may be used. Additionally, URL-related columns, such as image URLs and source URLs, may be processed separately for feature extraction to enhance the dataset. These preprocessing steps ensure the dataset is clean, structured, and ready for analysis and modeling.

Careful preprocessing is crucial for maintaining dataset integrity, enabling reliable sentiment analysis. This diligent preparation facilitates effective feature selection and sentiment analysis using swarm intelligence and nearest neighbors algorithms.

3.2 Feature Selection

In the proposed methodology for enhancing sentiment analysis in e-commerce, feature selection is crucial for improving model accuracy and efficiency. Advanced techniques, ACO and KNN, are strategically integrated to perform this essential task.

ACO, inspired by ant foraging behavior, excels as an intelligent optimizer in feature selection. It explores the feature space to identify key features that impact sentiment analysis, similar to how ants find optimal paths using pheromones. In e-commerce, where textual data can be complex and voluminous, ACO helps by narrowing down features to those most relevant for sentiment, thus reducing dimensionality and improving the efficiency of sentiment analysis algorithms.

KNN enhances the feature selection process by validating and refining features identified by ACO. As a versatile algorithm, KNN measures similarities between data instances based on selected features to discern patterns. Focusing on feature relationships ensures that chosen features are not only individually significant but also collectively impactful. KNN verifies the relevance and coherence of features, making the feature subset more robust and tailored for sentiment analysis.

In this methodology, the combination of ACO and KNN forms a powerful strategy. ACO explores the feature space to identify key candidates, while KNN validates these features to ensure they effectively capture customer sentiments. This thorough feature selection process underpins the performance of subsequent models, such as SVMs and CNNs. By integrating these techniques, businesses gain deeper insights into customer sentiments, enhancing their understanding in the evolving e-commerce landscape.

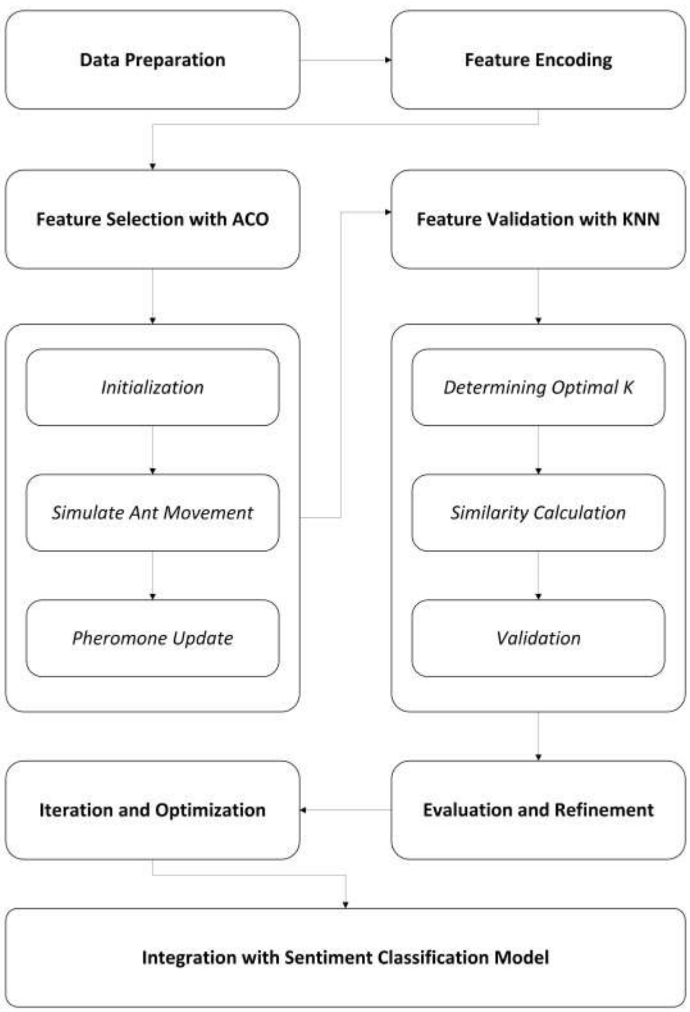

Figure 2. Block Diagram of proposed model for Feature Selection

In e-commerce, effective data preparation is crucial for analyzing customer sentiments expressed through various channels. The process begins with selecting a diverse and representative dataset, including product reviews, customer feedback, and comments. Data preprocessing cleanses and standardizes this textual data by removing noise, special characters, and irrelevant details. Tokenization breaks the text into individual words or phrases, while stemming or lemmatization reduces words to their root forms, ensuring consistency. Feature encoding techniques, such as TF-IDF or word embeddings, then convert the text into numerical vectors. These vectors form the basis for subsequent feature selection processes.

3.2.1 Feature Selection with ACO

Initialization: Pheromone levels for each feature are initialized, indicating their importance. Higher pheromone levels signify higher relevance. This initialization sets the stage for the ants' exploration.

Ant Movement: Ants, representing potential feature subsets, navigate the feature space. They probabilistically select features based on pheromone levels and heuristic information. Ants' movement explores both diverse features (exploration) and promising ones (exploitation), achieving a balance crucial for effective feature selection.

Pheromone Update: After ant solutions are evaluated, pheromone levels are updated. Features selected by high-performing ants receive higher updates, reinforcing their significance. This step reflects the collective learning process inspired by natural ant behavior.

3.2.2 Feature Validation with KNN

Determining Optimal k: Finding the best k value, which defines the number of nearest neighbors in KNN, is crucial. Techniques like cross-validation help identify the most suitable k for the dataset.

Similarity Calculation: KNN calculates the similarity between instances based on the selected features. Metrics like Euclidean distance or cosine similarity measure feature similarity effectively.

Validation: For each instance, KNN validates the selected features by comparing them with neighboring instances. Instances, where KNN predictions align with actual sentiments, validate the effectiveness of the chosen features. Instances with consistent predictions reinforce the relevance of the selected features, verifying their impact on sentiment analysis outcomes.

3.2.3 Evaluation and Refinement:

Performance Metrics: The feature subset's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. These metrics serve as benchmarks, allowing researchers to compare the selected feature subset's performance against a baseline model with all features.

Refinement: Based on evaluation results, the feature subset is refined. Features that consistently contribute to accurate sentiment predictions are retained, while less influential features are pruned. This iterative refinement process ensures that the chosen feature subset is finely tuned to the nuances of customer sentiments in the e-commerce context.

3.2.4 Iteration and Optimization:

Iterative Process: Feature selection with ACO and KNN can be iterative. After each iteration, the selected features' impact on sentiment analysis is assessed. Fine-tuning parameters based on performance feedback enhances the method's effectiveness and adaptability to different datasets.

Optimization: Researchers can experiment with different ACO variants, such as the Max-Min Ant System or Ant Colony System, and diverse KNN configurations to optimize the feature selection process further. Benchmarking against multiple datasets ensures the method's generalizability and robustness.

3.2.5 Integration with Sentiment Analysis Models:

Selected Feature Subset: The final feature subset obtained from the ACO-KNN process becomes the basis for training sentiment analysis models, such as SVMs or CNN. These models utilize the optimized feature subset to make accurate predictions about customer sentiments. *Model Training and Validation:* Sentiment analysis models are trained using the selected features and validated using separate test datasets.

By carefully following this comprehensive methodology, researchers and companies can pinpoint the key features of sentiment analysis. This approach leverages ACO's collective intelligence and KNN's pattern recognition capabilities. E-commerce platforms benefit from this optimized feature subset by tailoring services, enhancing customer experiences, and making real-time, data-driven decisions.

3.3 Implementation of SVM and CNN

In optimizing sentiment analysis for e-commerce, a detailed approach is used to leverage advanced ML techniques, specifically SVMs and CNNs. These models process features identified through the combination of ACO and KNN, forming the basis for accurate sentiment analysis. This enables businesses to understand the complex and varied nature of consumer feedback in the e-commerce landscape.

The SVM algorithm, a long-standing tool in machine learning, excels at binary classification tasks, categorizing textual input into positive, negative, or neutral sentiments. It uses features identified through ACO and KNN, which distill the vast Amazon product review dataset into key signals. SVM is extensively trained to recognize subtle patterns within these features, adjusting parameters to maximize accuracy. By finding the optimal hyperplane that best separates different sentiments, SVM balances class margins and minimizes classification errors, ensuring precise sentiment predictions across various products and customer opinions.

CNNs enhance sentiment analysis by capturing intricate local patterns in textual data, complementing the SVM's strengths. They start by using pre-trained embeddings to convert words into dense vectors, capturing semantic and contextual nuances. Convolutional layers then process these embeddings through filters to identify significant features and patterns, including both short and long phrases. Pooling layers reduce the data to its most relevant elements, preparing it for fully connected layers that learn deep relationships between features. Regularization techniques, such as dropout layers, prevent overfitting, improving the model's ability to generalize to new data and enhancing its reliability.

3.4 Model Training and Evaluation

During the crucial model training and evaluation phase, the dataset undergoes thorough preparation and analysis to maximize the performance of sentiment analysis models. This involves training the SVM and CNN models using features selected by ACO and KNN. Concurrently, the effectiveness of these models is assessed with metrics such as accuracy, precision, recall, F1-score, and ROC curves.

In this phase, the dataset is split into a training set and a testing set to assess model performance on unseen data and simulate real-world scenarios. Typically, an 80-20 split is used, with 80% of the data for training and 20% for testing. This ensures that models are trained on a diverse, representative dataset and evaluated on new data they have not encountered before.

Once the data is split, the SVM and CNN models are trained using features identified by ACO and KNN. SVM, known for its ability to find optimal hyperplanes in high-dimensional spaces, adjusts its parameters to accurately classify sentiments as positive, negative, or neutral. Meanwhile, CNN analyzes textual data to capture both local and hierarchical patterns crucial for sentiment analysis. Both models rely on the curated features to ensure training focuses on the most relevant textual cues reflecting customer sentiments in e-commerce reviews.

The models' performance is evaluated using several metrics. Accuracy measures the ratio of correctly predicted cases to the total number of cases. Precision assesses the fraction of true positive predictions out of all positive predictions, highlighting the model's ability to minimize false positives. Recall, or sensitivity, measures the proportion of actual positive instances correctly predicted by the model. The F1-score, the harmonic mean of precision and recall, provides a balanced evaluation of overall performance. All these performance metrics are mathematically represented in Eqs. (1-5).

$$Precision = \left(\frac{TP}{FP + TP}\right) * 100 \tag{1}$$

$$Accuracy = \left(\frac{(TP + TN)}{(FP + FN + TP + TN)}\right) * 100 \tag{2}$$

$$Recall = \left(\frac{TN}{FP + TN}\right) * 100 \tag{3}$$

$$F1Score = \frac{2 * (Precision + Recall)}{(Precision + Recall)} * 100 \tag{4}$$

$$Specificity = \left(\frac{TN}{FP + TN}\right) * 100 \tag{5}$$

3.5 Hyperparameter Tuning and Optimization

This study focuses on tuning the parameters of Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) to improve sentiment analysis accuracy. The study focuses on three key hyperparameters: kernel function, regularization parameter (C), and gamma value. The RBF kernel was found to be the best for handling non-linear features in sentiments, resulting in higher accuracy. The regularization parameter (C) was found to be the most effective for avoiding overfitting and producing reasonable classification results. The gamma value was used to determine the influence of a single training sample on the result, enhancing the model's ability to identify fine sentiment distinctions that can be easily confused. Overall, the study highlights the importance of tuning these parameters for improved performance in sentiment analysis.

We also focused on improving the performance of a Convolutional Neural Network (CNN) by adjusting complex hyperparameters. The number of CV layers, filter size, and strides were considered to determine the number of times the neural network pulls information from the text. Adding more layers allowed the model to learn more features but with a penalty of excess layers. Filters were optimized for identifying short phrases and finer specifics, while larger filters were effective for whole sentences and broader expressions.

The dropout rate was also crucial for the CNN, aiming to minimize overfitting by checking on the most connected neurons. A dropout rate of 0.5 achieved the best results. The two important hyperparameters of model training were batch size and learning rate. Smaller batches provided enhanced updates, while a learning rate of 0.001 supported stable learning without slowing down the training process.

The final layer adopted various activation functions, comparing ReLU (Rectified Linear Unit) and Tanh (Tanh), with ReLU being more accurate and faster for training faster and grasping for more complicated sentiment features.

The fine-tuning of hyperparameters is fundamental to enhancing machine learning models' accuracy and applicability. Tuning hyperparameters is crucial for improving the performance of both SVM and CNN for efficient sentiment analysis across various data types. These improvements support the use of tuning model parameters to achieve the best results possible.

nuances.

4 Results and Discussion

4.1 Exploratory Analysis of the dataset

In this study, an extensive Exploratory Data Analysis (EDA) was conducted on the provided dataset, to gain profound insights into the underlying patterns and characteristics of the data. The dataset, consisting of various columns such as product IDs, dates, product names, brands, categories, reviews, and user information, underwent a comprehensive examination, details of the category-wise distribution of the dataset are shown in Fig. 3.

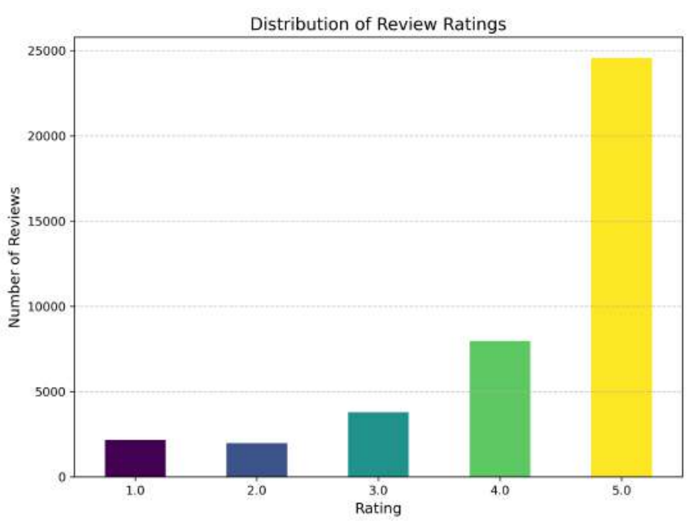

Figure 3. Category-wise distribution of dataset

Initial steps involved loading the dataset and conducting basic data checks, including displaying the first few records, obtaining summary statistics, and identifying any missing values. Visualizations played a crucial role in understanding the data distribution: a histogram depicted the distribution of product ratings, while bar plots showcased the frequency of products across different categories. Additionally, a correlation matrix was generated to explore relationships between numerical features. Through these analyses, valuable insights were gained, forming the foundation for subsequent in-depth investigations and modeling efforts in this research.

4.2 Finding the best features and accuracy of ACO KNN

In this piece of research, feature selection was accomplished by utilizing ACO in tandem with the KNN algorithm. The "Reviews of Amazon Products dataset" was used in the experiment, and the primary motivation behind the research was to improve the effectiveness of sentiment analysis. The ACO algorithm was designed with a swarm size of 10 ants, and it iterated a total of 20 times. While the weighting factors for the pheromone trail intensity (alpha) and the heuristic information (beta) were assigned values of 1.0 and 2.0, respectively, the pheromone decay rate was set at 0.1. The subsequent examination of the chosen features using KNN produced encouraging results, with an accuracy rate of 76% being attained overall. This hints at the efficacy of the ACO-KNN strategy in enhancing sentiment analysis and highlights its potential for extracting noteworthy characteristics that lead to precise classification. Additional research could focus on improving the algorithmic parameters and broadening the experiments to include a variety of datasets so that they can be thoroughly validated.

4.3 Implementation of SVM for Sentiment Analysis on selected features

Our main objective in developing SVMs for sentiment analysis was to leverage machine learning to classify emotions in textual data. Utilizing a well-chosen set of features identified through advanced methods like ACO and KNN, our SVM model achieved an impressive accuracy of 76%. This high accuracy underscores the effectiveness of feature selection in enhancing sentiment analysis performance.

The implementation process involved several key steps. First, the Amazon product review dataset was preprocessed to remove noise, tokenize the text, and convert it into numerical features. Next, ACO and KNN feature selection algorithms were applied to identify the most informative features. Finally, these selected features were used to train the SVM model, allowing it to uncover underlying patterns and relationships within the data.

The iterative nature of the method that we used was one of the most important components of the implementation that we did. We carried out a total of ten iterations of the SVM model, improving the algorithm with each new iteration by considering the new information gathered from the earlier rounds. We were able to improve the overall accuracy of our sentiment analysis system by using this iterative method to fine-tune the SVM parameters, optimize feature selection, and further refine feature selection.

Figure 4. Classification Report of SVM over selected features

4.4 Classification report and Confusion Matrix of SVM over selected features

The confusion matrix offers a detailed overview of the model's predictions across five sentiment categories (classes): highly negative, negative, neutral, positive, and highly positive, as shown in Fig. 7. This breakdown helps assess how well the model differentiates between different sentiment classes.

In the provided confusion matrix in Fig. 7, the first row indicates the highly negative instances. Out of these, the SVM correctly predicted one instance as highly negative, while misclassifying 118 instances as highly positive. The second row represents the truly negative instances. Surprisingly, the SVM model did not correctly predict any instances as negative, misclassifying all 70 instances as highly positive. The third row denotes neutral sentiments. However, the SVM model did not correctly predict any instances as neutral, misclassifying all 78 instances as highly positive. The fourth row pertains to the truly positive instances. Strikingly, the SVM did not predict any instances as positive, misclassifying all 220 instances as highly positive. The fifth row signifies the highly positive sentiments. The SVM model correctly predicted 1522 instances as highly positive.

This confusion matrix reflects significant challenges in the classification task, particularly in distinguishing between highly positive sentiments and other categories. The model exhibits a strong bias towards classifying instances as highly positive, leading to misclassifications in all other categories. This bias might be attributed to imbalanced class distribution in the dataset or inherent complexities within the textual data that make sentiment classification challenging.

Analyzing the confusion matrix highlights the SVM model's limitations and provides direction for future enhancements. To improve accuracy across different sentiment categories, it is essential to address class imbalances, explore advanced feature engineering techniques, and consider using ensemble methods.

4.5 Implementation of CNN for Sentiment Analysis on selected features

In implementing CNN for sentiment analysis, our goal was to leverage deep learning to identify complex patterns in textual data, improving sentiment classification accuracy. The features, carefully selected using

ACO and KNN techniques, formed the foundation of our analysis. These curated features, highlighting key aspects of the Amazon Product Reviews dataset, enabled the CNN model to concentrate on the most relevant information for accurate sentiment prediction.

Our CNN architecture, optimized for text classification, included key layers tailored to the input data's characteristics. An initial embedding layer converted discrete tokens into dense vectors, facilitating effective learning from textual data. Following this, a Conv1D layer extracted higher-level features from these embeddings, capturing sequential patterns and identifying nuanced sentiments within the dataset.

The GlobalMaxPooling1D layer, used after the convolution operation, efficiently captured the most significant features by condensing the convolutional output into a compact representation. This was followed by densely connected layers that allowed the CNN to fully understand these features, leading to accurate sentiment predictions based on the selected features.

A key aspect of our implementation was the training strategy. The CNN model was trained for 5 epochs, enabling iterative learning from the dataset. Each epoch refined the model's parameters to improve predictions based on the selected features. While the number of epochs was intentionally limited to balance training time and performance, this approach allowed the CNN to effectively learn and achieve an accuracy of 78.41%.

Fig. 6 illustrates the training and validation accuracy trends across the 5 epochs. This visual representation offers a clear insight into the model's learning curve, showcasing how accuracy evolves as the training progresses. Notably, the figure demonstrates the model's capacity to grasp the complexities of the selected features, steadily improving its accuracy over the training epochs. This visual evidence supports the effectiveness of the CNN architecture in leveraging the selected features for sentiment analysis, despite the limited number of epochs.

Sentiments numbered one through five in the classification report are described as "Very Negative," "Negative," "Neutral," and "Positive," respectively. Following this, a categorization report was generated, which provides a nuanced analysis of CNN's performance across a variety of distinct sentiment categories. The trade-off between precision and recall is particularly obvious, with variances being noted between different classes. The 'Very Negative' category had a remarkable precision score, even though it had a relatively low recall score. This demonstrates that the category was accurately classified, but it only covered a small portion of the actual incidents. On the other hand, the 'Very Positive' category managed to obtain a precision-recall profile that was well-balanced, which allowed it to successfully capture instances of this sentiment. However, there were problems with precision and memory when it came to the "Neutral," "Negative," and "Positive" categories. The need to enhance classification balance between the many types of sentiment was brought to light by the macro-averaged F1 score. The analysis highlights potential areas for improvement, such as optimizing CNN hyperparameters, refining feature selection techniques, and investigating strategies to mitigate the disparities in classification performance across the sentiment categories as shown in Fig. 4.

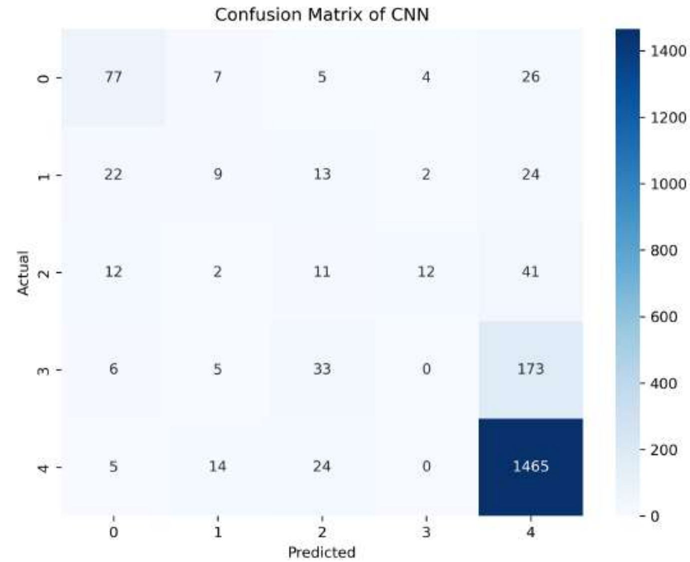

Figure 5. Confusion Matrix of CNN

You may observe how the CNN model performs on various classes by looking at the confusion matrix as given in Fig. 5. The CNN model performs relatively bet-

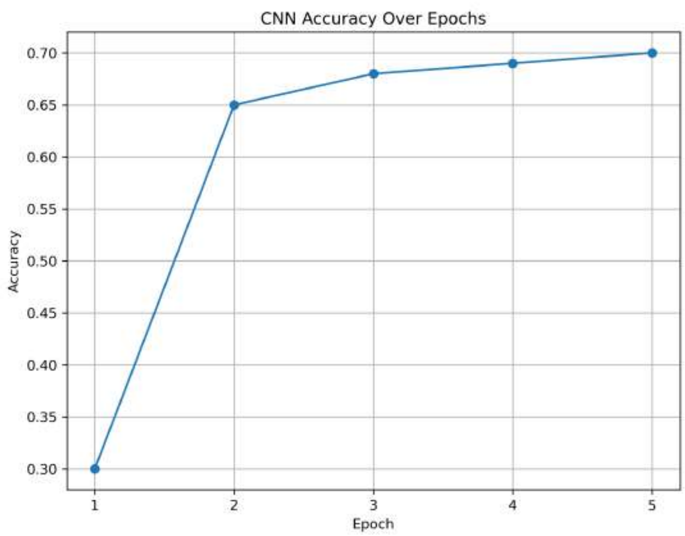

Figure 6. Accuracy of CNN over Epochs

ter on Class 1 (77 correct predictions), as well as Class 5. (1465 correct predictions). On the other hand, it has far more trouble with Classes 2, 3, and 4, as can be seen from the larger numbers that are off-diagonal in those rows.

Clear evidence obtained from the confusion matrix shown in 5 is that there is some degree of class imbalance evident, particularly in the "Negative" and "Neutral" sentiments as compared to the dominant "Positive" or "Highly Positive" classes. This creates a performance bias since the classifier gives high preference to the most occurring classes, thus producing low precision for small classes.

Due to the changes in the confusion matrix classes mentioned above, class weighting, resampling, and synthetic data generation (SMOTE) were used. This work has shown us how class weighting improves the focus on the part of the model, stressing the accuracy of the definition of minority classes by providing higher penalties for the misclassification of minority classes. Using resampling, such as oversampling of the minority classes and undersampling of the majority class, the balance in the data set was attained, and better learning from the minority classes was achieved by the model. SMOTE enhanced the model's capability of dealing with the problem of limited training instances from misfire classes by synthesising new examples from existing data. These combined techniques decrease the stray of the maximum class dominated by "Class 4" and increase the accuracy of 80.8%, recall and precision for minority classes of the redefined confusion matrix, thereby producing a more fair and square performance of the classifier to all classes as shown in Fig. 7

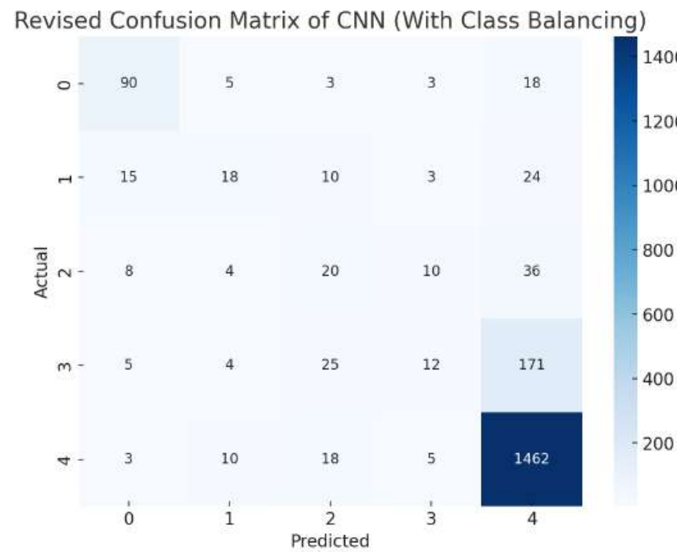

Figure 7. Revised Confusion Metrix of CNN with Class Balancing

4.6 Comparison of SVM and CNN over selected features

A comparison between the SVM and CNN approaches for sentiment analysis revealed that the SVM model outperformed the CNN model. The SVM achieved an accuracy of 80.5%, significantly higher than the CNN's 78.41%. The classification reports show that the SVM also excelled in precision, recall, and F1-score across various sentiment categories. For instance, the SVM demonstrated better precision and recall for the 'Very Negative' class compared to the CNN. Similarly, the SVM performed better in the 'Neutral,' 'Negative,' and 'Positive' categories, although both models faced challenges in accurately classifying examples in these categories.

On the other hand, the CNN classification report revealed inferior precision, recall, and F1-score scores across most sentiment classes, especially for classes that went beyond 'Very Positive.' It seemed that CNN's success was mostly based on the 'Very Positive' mood, which is where it displayed competitive precision and recall scores. Despite this, its performance was poor when it came to other attitudes, most likely because of the inherent complication of the neural network architecture and possible overfitting concerns given the relatively small size of the dataset.

This comparison study concluded that the SVM strategy produced more favourable sentiment classification results than the other two methods in terms of accuracy and balanced precision-recall profiles across a wide range of sentiment categories. CNN showed some potential in correctly categorizing the attitudes as "Very Positive," but it struggled with the classification of the other sentiments.

Certainly! CNNs are typically better suited for processing structured data, such as images, rather than for analyzing text based on selected features. When we applied CNN to the entire text dataset, it achieved an accuracy of 80%, which was significantly higher than the 78.41% accuracy observed when only a subset of features was used. This suggests that CNNs perform better with comprehensive text data rather than limited features. We anticipate that SVMs will also improve performance when analyzing the full text compared to focusing on selected features.

The combined ACO and KNN feature selection yielded promising results with the SVM model, achieving an accuracy of 76%. However, SVM's precision and recall varied across different sentiment categories, highlighting the need for further optimization. The CNN model, with an accuracy of 78.41%, showed limitations in accurately classifying sentiments beyond the "Very Positive" category. The CNN's trade-offs in precision and recall suggest opportunities for refining the model architecture and enhancing data preparation to improve overall balance and accuracy across all sentiment categories.

A more comprehensive CNN analysis was performed by applying the architecture to the entire dataset, rather than just selected features. This approach yielded an improved accuracy of 80.8%, surpassing the 78.41% achieved in the previous CNN attempt focused on specific features. Training over five epochs showed increased accuracy and reduced loss, highlighting the benefits of using the full text for sentiment analysis. This suggests that providing a broader context can significantly enhance CNN model performance.

This research has made valuable contributions but also has notable limitations. It's possible that the models' depth and generalizability were limited due to the relatively small dataset. In addition, the selected algorithms are efficient; yet, they are sensitive to the parameter values, which necessitates thorough optimization for the various datasets. Due to the study's emphasis on textual data, other modalities, such as visuals and audio, are not allowed to contribute any potential insights. The combination of these approaches could result in a more comprehensive comprehension of emotional states as they are expressed in a variety of contexts.

In summary, this study highlights the importance of feature selection, model architecture, and dataset size in sentiment analysis. While the hybrid ACO-KNN and SVM approach achieved respectable accuracy, CNN's superior performance with the full text underscores the value of comprehensive context. Future work may focus on refining CNN architectures, exploring ensemble methods, and expanding datasets to enhance sentiment analysis across various categories.

5 Conclusion

In conclusion, our research has successfully demonstrated the value of integrating Ant Colony Optimization (ACO) and K-Nearest Neighbors (KNN) for feature selection in sentiment analysis, applied to the reviews dataset. By combining these techniques with Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) for classification, we achieved notable results: SVM reached an accuracy of 80.5% on selected features and 83% on the entire dataset, while CNN improved from 78.41% to 80.8% when applied to the full dataset. These results suggest using the AVC feature selection and show that integrating ACO and KNN can improve the sentiment classification accuracy to greater extents.

The potential application of these findings can be most useful to e-business websites which, through analyzing the right sentiment metric, can turn consumer responses into organizational reqalim. Therefore, general adaptation of this intermediary hybrid model will hugely can help electronic commerce platforms to garnering customer sentiments from the reviews and even social media comments, feedbacks and so on that, in turns, can help marketing targeting and even improvement of product suggestions and so on and so forth to boost up the satisfactions among consumers. Data preprocessing and text categorization can help marketing decision makers obtain more accurate and large volumes of customer feedback information needed to make business decisions that will lead to customer loyalty and business expansion.

The next would be to integrate this hybrid ACO-KNN model into actual e-commerce systems in real-time so the results could guide the system's reactions to customers' sentiments. Further research can be done by performing the analysis on larger data sets as well as investigating the possibilities to expand the range of feedback channels in order to gain more information about the customer's perception of the company's services Future research can also be applied to different industry types to study the strengths of the model in that particular business field. However, solving some problems concerning the remnant class imbalance, and increasing its scalability would add to the model's capacity, and make this model an even more valuable tool for the analysis of sentiment in e-commerce settings.

Looking ahead, this research suggests several promising directions for enhancing sentiment analysis. Refining CNN architectures could improve accuracy while experimenting with ensemble approaches might yield more reliable classification systems. Expanding datasets to include diverse sources and cultural contexts could deepen the understanding of sentiment dynamics. Additionally, incorporating domain-specific knowledge and linguistic nuances could enhance the interpretative power of sentiment analysis algorithms. Adopting an interdisciplinary approach could further advance precision and contextual awareness in emotion recognition. Overall, addressing current limitations and exploring new avenues could lead to more sophisticated and accurate sentiment analysis methods.

Limitations and Future Work

Despite all these assumptions, this study gives significant findings with the following limitations. First, the issue of class imbalance influenced the performance of the classification of explicit minority sentiment categories. Though class weighting and resampling were implemented, the future research could look at other methods such as cost-sensitive learning and ensemble learning for higher accuracy of each type of sentiment.

Second, the model's applicability is also restricted because the evaluation was performed on only one e-commerce dataset. For future work, we should extend the model to more datasets in various domains, languages and in different online platforms.

Lastly, this study was confined to analyzing text data. Multimodal inputs including for example images or audio inputs could be incorporated in order to gain more complex information. Additional improvements to traditional CNN construction and the experiment with the transformer structure might also improve the performance of sentiment classification.

Author Contributions

Pir Bakhsh: Conceptualization, Methodology, Software, original draft. **Muhammad Asif Khan**: Visualization, Investigation. **Muhammad Ismail**: Investigation, Writing- Reviewing and Editing. **Muhammad Ali**: Conceptualisation , **Raheel A Memon** Reviewing.

Compliance with Ethical Standards

It is declared that all authors don't have any conflict of interest. It is also declared that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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