Journal of Information Systems and Informatics
Vol. 7, No. 3, September 2025 e-ISSN: **2656-4882** p-ISSN: **2656-5935**
DOI: 10.51519/journalisi.v7i3.1222 Published By DRPM-UBD

Impact of NLP Algorithms on Sentiment Analysis Efficiency and Accuracy

Puas Triawan[1], Imam Tahyudin[2], Purwadi[3]

[1,2,3]Master of Computer Science Study Program, Faculty of Computer Science, Amikom University Purwokerto, Indonesia
Email: [1]puastriawan@gmail.com, [2]imam.tahyudin@amikompurwokerto.ac.id, [3]purwadi@amikompurwokerto.ac.id

Abstract

Sentiment analysis plays a crucial role in understanding user perceptions of products and services in the digital era. However, its implementation is still constrained by the need for high computational resources. This research aims to evaluate the impact of implementing transformer-based Natural Language Processing (NLP) algorithms—such as BERT, RoBERTa, and ELECTRA—on the quality and efficiency of sentiment analysis, especially in multilingual and real-time data contexts. This study uses a Systematic Literature Review (SLR) approach with the PRISMA protocol to assess the performance, challenges, and solutions offered by various NLP models. The study results show that transformer-based models consistently outperform traditional approaches; BERT and RoBERTa can achieve accuracy above 95% with F1-scores ranging from 0.92–0.95, while ELECTRA records the highest accuracy up to 98.09% with average precision and recall above 0.90 on e-commerce data. Furthermore, the transfer learning approach has been proven to reduce training time by 50–70% compared to conventional methods, without compromising analysis quality. Nevertheless, the need for large computational power remains a major obstacle. Several strategies, such as model distillation and data augmentation, have proven effective in reducing computational load while maintaining high performance. These findings confirm that transformer-based NLP technology not only improves the quality of sentiment analysis but also opens up innovation opportunities for cross-language and cross-domain applications. This research recommends optimizing models for resource-constrained languages and developing real-time systems to achieve inclusivity and efficiency in modern data processing.

Keywords: Sentiment Analysis, NLP, Transformer, Multilingual, Computational Efficiency, Transfer Learning, Systematic Literature Review

1. INTRODUCTION

Natural Language Processing (NLP) is a branch of artificial intelligence that focuses on how machines can understand, process, and generate human language. In the last decade, the development of NLP has driven rapid advancements in various text-based applications, one of which is sentiment analysis. This analysis is used to identify users' opinions, emotions, and attitudes towards a particular

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

product, service, or issue. The relevance of sentiment analysis is increasingly high in the digital era, especially with the growing volume of textual data sourced from social media, online forums, and customer reviews [1],[2].

Various methods have been applied for sentiment analysis. Early approaches based on lexicons and classic statistical algorithms, such as Naive Bayes or Support Vector Machines, were once the main standard. However, these methods were less capable of capturing semantic complexity, such as irony or context dependent on word order, thus limiting their performance [3],[4]. The advancement of deep learning then gave rise to models like CNN and LSTM, which offer deeper text representations [19]. Although more accurate, these models require large amounts of data, long training times, and high computational resources, making them inefficient when applied on a large scale or in domains with limited data.

As an alternative, the transfer learning approach emerged, utilizing pre-trained models such as BERT, RoBERTa, and ELECTRA. These models have proven superior in understanding semantic context while being easily adaptable to various sentiment analysis domains [5]. Recent studies show that transfer learning can cut training time by 50–70% while maintaining consistent accuracy above 90% [6], [7]. In fact, ELECTRA has been reported to achieve accuracy up to 98.09% on e-commerce data, with average precision and recall values exceeding 0.90 [3]. This advantage makes transfer learning relevant for multilingual and real-time applications, which are increasingly needed in modern practice [8].

Nevertheless, the implementation of transfer learning is not without challenges. Large pre-trained models require advanced computational infrastructure, while the fine-tuning process still needs high-quality annotated data to avoid overfitting. Additionally, limitations in model interpretability are an important issue, especially in sectors that demand high transparency such as healthcare, finance, and public policy [9], [10]. Several previous literature reviews have indeed discussed the development of sentiment analysis [11], [12]. However, most still focus on comparing traditional methods with classic deep learning or on specific limited domains. A research gap arises from the lack of a systematic study highlighting the effectiveness of transfer learning in domain-specific, multilingual, and real-time sentiment analysis.

Considering these points, this research has two main objectives. First, to conduct a Systematic Literature Review (SLR) using the PRISMA protocol to evaluate the extent to which transfer learning can improve training efficiency and the quality of sentiment analysis results. Second, to identify technical challenges and optimization strategies, such as model distillation and data augmentation, that can encourage wider utilization of transfer learning in both academic and industrial realms. Thus, this research is expected to contribute theoretically and practically to

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

the development of more inclusive, efficient, and adaptive sentiment analysis systems in the modern data era.

2. METHODS

2.1. Research Methods

In this systematic literature review, the research questions were formulated based on the PICOC (Population, Intervention, Comparison, Outcome, and Context) approach to ensure that the scope of the study was focused and comprehensive. This approach was used to determine the scope of the analysis, the technological approach used, and the comparison of the effectiveness of various methods in the context of sentiment analysis based on Natural Language Processing (NLP). The population of interest in this study was text data from various digital platforms such as social media, consumer review systems, and online forums, which contained opinions and expressions of sentiment from users in various languages and domains. The intervention in this research involves the use of state-of-the-art transformer-based NLP models—such as BERT, RoBERTa, and GPT—adapted through transfer learning techniques to improve accuracy and efficiency in processing large-scale, multilingual data that is context-specific. As a comparison, conventional NLP approaches such as LSTM, CNN, and traditional lexicon-based classification and machine learning techniques are used to assess the relative advantages of transformer models. The expected results include an assessment of the performance of transformer models in multilingual scenarios, the identification of challenges in real-time sentiment analysis, and the measurement of the effectiveness of transfer learning in accelerating the training process without compromising the quality of the results. The context of this research is the application of NLP to evaluate public opinion in real-time, domain-based data, with the aim of supporting data-driven decision-making. Based on this framework, this study aims to answer three main questions:

1) RQ1: How does the performance of NLP-based transformer models such as BERT in analyzing multilingual sentiment compare to traditional approaches, particularly in terms of accuracy and efficiency?
2) RQ2: What are the biggest challenges in implementing NLP models for sentiment analysis on real-time data, and how can data streaming techniques overcome these limitations?
3) RQ3: How effective is transfer learning in accelerating the training of NLP models on domain-specific sentiment datasets without compromising the quality of the analysis results?

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

2.2. Search Strategy

The literature search process was conducted systematically through several leading academic databases, namely IEEE Xplore, ScienceDirect, and MDPI. These sources were selected based on their coverage of high-quality scientific publications and their relevance to the field of information technology. A combination of keywords and Boolean operators was used to ensure comprehensive search results. The search focus was limited to the years 2021-2025 to ensure the relevance and recency of the research. The search process followed the following steps:

1) Keywords were identified based on the main topic and related terms (e.g., sentiment data, data analysis, NLP, sentiment analysis).
2) Keywords are used with Boolean operators such as AND, OR, NOT to expand or narrow the scope of the search.
3) Initial search results are filtered based on relevant titles and abstracts.
4) Further selection is conducted to ensure the literature aligns with the research focus.

Table 1 shows the combination of keywords and Boolean operators used for literature searches in MDPI, IEEE Xplore, and ScienceDirect. This combination is designed to cover research on the influence of NLP algorithms on the quality and speed of sentiment analysis. The results of this table ensure that the search coverage includes NLP methods such as BERT, LSTM, and CNN and their applications in sentiment analysis data. The use of specific keywords such as "sentiment data" and "data analysis" helps focus the search results on current trends in sentiment analysis and NLP.

Table 1. Boolean Sources and Keywords

Sources	Boolean Keywords
MDPI	("Sentiment data") AND ("Data analysis") AND ("NLP")
IEEE Xplore	("Sentiment data") AND ("Data analysis") AND ("NLP")
ScienceDirect	("Sentiment data") AND ("Data analysis") AND ("NLP")

2.3. Study Selection

The literature selected for this review was screened based on strict inclusion and exclusion criteria. These criteria ensured that only relevant and recent studies were considered for inclusion. Table 2 summarizes the inclusion and exclusion criteria used to screen the literature in this study. The articles included focused on the

Journal of Information Systems and Informatics
Vol. 7, No. 3, September 2025

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

influence of NLP algorithms on the quality and speed of sentiment analysis, were published between 2021 and 2025, and provided empirical evaluations with clear metrics. Articles in languages other than English. The application of these criteria ensures that only relevant and high-quality articles are analyzed, thereby supporting the research focus on current trends and the implementation of NLP in sentiment analysis data.

Table 2. Inclusion and Exclusion Criteria

Inclusion	Exclusion
Publications from 2021 to 2025	Publications prior to 2021
English articles or valid translations	Articles in languages other than English without translation
Unstructured text datasets from social media (Twitter, Reddit), product reviews (Yelp, IMDB), or news articles.	Synthetic or irrelevant datasets for sentiment analysis (e.g., visual or numerical data)
Articles discussing the impact of text preprocessing (tokenization, stemming, lemmatization) on algorithm performance in sentiment analysis.	Research that does not mention performance metric evaluation in terms of both quality and speed
Articles published in peer-reviewed journals or reputable scientific conferences.	Articles from unverifiable sources (e.g., blogs, white papers, or publications without peer review)
Empirical studies evaluating NLP algorithms for sentiment analysis, with a focus on quality metrics (accuracy, precision, recall, F1-score) and processing speed (runtime, latency).	Conceptual studies or literature reviews that do not include experiments or quantitative evaluations

2.4. Quality Assessment

The next step in SLR research is quality assessment. This process can be visualized using a PRIMA diagram as shown in Figure 1. The aim is to ensure the accuracy and relevance of the research collected to the topic under review, thereby producing appropriate SLR conclusions [13].

During the journal quality assessment phase, several questions can be formulated to evaluate the quality of each journal. The four criteria for assessing the quality of each journal are as follows:

1) Is this article relevant to the topics of sentiment analysis and the speed of NLP algorithm usage?
2) Does the research clearly describe the methods/algorithms used?

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

3) Does the research use appropriate evaluation metrics for predicting the speed of NLP algorithms in handling sentiment analysis data?
4) Are the conclusions supported by the results obtained and are the implications clear?

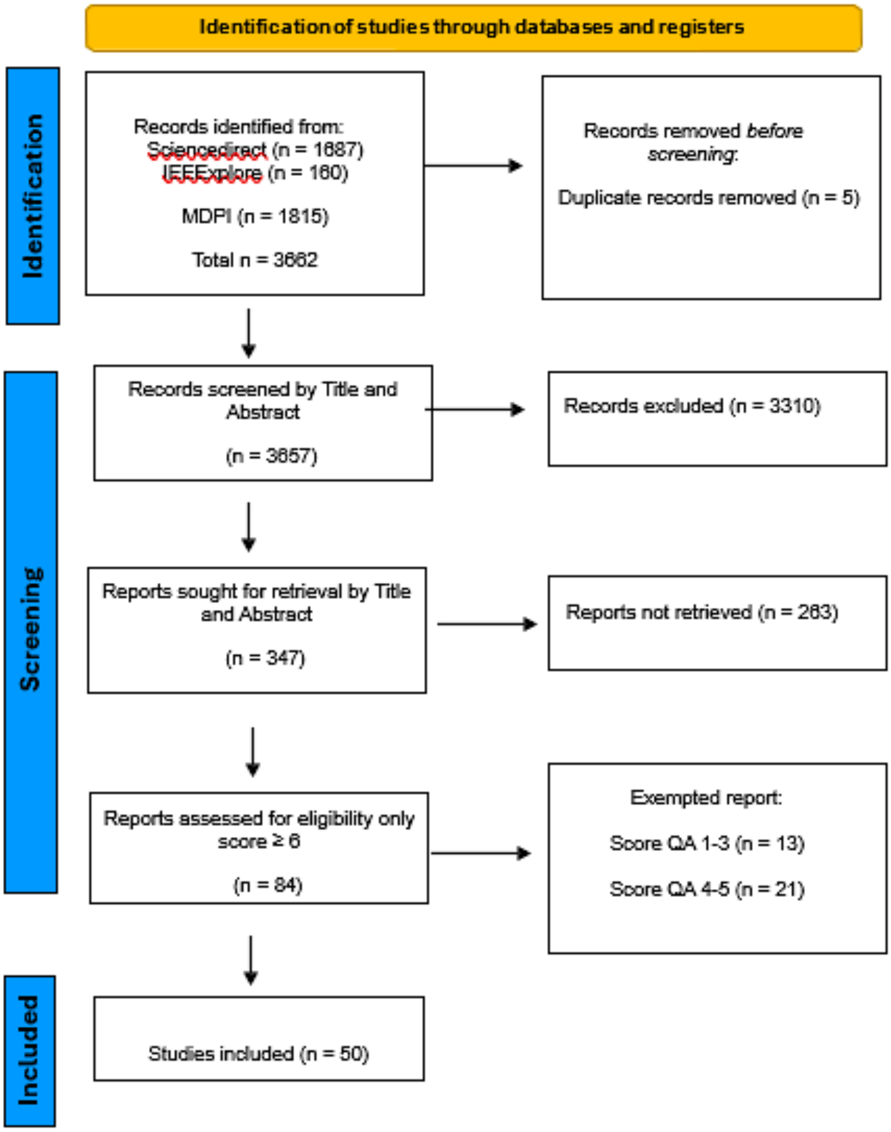

Figure 1. The systematic process used in this literature review.

Literature searches were conducted through the IEEE Xplore, ScienceDirect, and MDPI databases for publications from 2021–2025. The search process used

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

keywords such as "Data Analysis", "Sentiment Data", "NLP", "Sentiment Analysis", and "Natural Language Processing", combined with Boolean operators to expand the scope of results. From a total of 3,662 articles found, 347 articles were filtered based on title and abstract. Subsequently, through a more in-depth quality assessment, 50 relevant articles were selected for analysis. Non-scientific articles, publications without evaluation results, and research that only discussed conventional methods were not included in the study. Each selected article was then evaluated based on topic relevance, methodological clarity, the use of evaluation metrics such as MAE and MAPE, and the practical contribution of the research findings.

This study adopted a descriptive analysis approach to identify patterns, trends, challenges, and solutions related to the application of NLP algorithms in improving the quality and speed of sentiment analysis. The selection process followed the PRISMA protocol, resulting in 50 articles that formed the basis of the analysis. The study results focused on the performance of transformer-based models in NLP, implementation challenges, proposed solutions, and the effectiveness of transfer learning approaches in sentiment analysis.

3. RESULTS AND DISCUSSION

3.1. RQ1: How does the performance of NLP-based transformer models such as BERT compare to traditional approaches in analyzing multilingual sentiment, particularly in terms of accuracy and efficiency?

This research question highlights the comparison of the performance of NLP-based transformer models such as BERT with traditional approaches in analyzing multilingual sentiment, particularly in terms of accuracy and efficiency. The results of the study show that BERT consistently excels at capturing complex semantic relationships across multiple languages. In various studies, BERT achieved an accuracy of up to 95%, surpassing approaches such as LSTM and Random Forest, which are limited in understanding deeper contexts and handling data with irregular structures [5], [13]. BERT's superior capabilities stem from its transformer architecture, which leverages the attention mechanism. This mechanism enables the model to simultaneously process large amounts of data, offering significantly higher speed compared to sequential-based methods like LSTM [13]. For example, research by Prottasha et al. highlights that transfer learning with BERT not only accelerates training but also improves accuracy by leveraging pre-trained parameters [13].

In a multilingual context, transformer models like BERT demonstrate high flexibility. This approach addresses the challenges of languages with limited

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

resources through data augmentation, as demonstrated in sentiment analysis on the Turkish language. The results show a significant improvement in accuracy, proving that this model can be adapted for languages with limited datasets [4]. Additionally, BERT's ability to capture the semantic meaning of unstructured data, such as customer reviews on e-commerce platforms or social media, provides deeper insights into global customer perceptions [14]. However, there is a significant drawback related to resource efficiency. The training and inference processes of Transformer-based models require advanced computational infrastructure, including GPUs or TPUs. This challenge can be a barrier for organizations with limited technological resources. To address this, a hybrid approach has been proposed, where transformers are combined with lexicon-based methods to improve operational efficiency without sacrificing accuracy [9]. Furthermore, when applied to cross-domain tasks, Transformer models offer advantages that traditional methods do not have. Their ability to capture specific sentiment patterns from various domains such as finance, e-commerce, or healthcare demonstrates that these models have high flexibility in various application contexts [14], [9].

Table 3. Conclusions and Implications

Aspect	Conclusion	Implications
Accuracy Performance	Transformer models such as BERT and ELECTRA provide high accuracy, reaching 98.09% in sentiment analysis across various domains and cross-language datasets [13][8][6].	Providing accurate and in-depth analysis results, supporting data-driven strategic decision-making in the business, education, healthcare, and other sectors.
Time Efficiency	The transformer architecture, with its parallel processing mechanism, enables fast processing of large-scale data, although it requires significant computational resources [13][9][10]	Accelerating big data analysis for real-time decision-making, but requiring additional investment in technology infrastructure such as GPUs/TPUs.
Multilingual Capabilities	Transformer models excel at handling multilingual data, including languages with limited resources such as Uyghur and Turkish, through an adaptive approach [4][15][16]	Enabling cross-language sentiment analysis, expanding global application reach, and supporting the development of underrepresented language technologies.
Unstructured Data	Transformers are highly effective for analyzing unstructured data, such as social media reviews and domain-specific texts, including	Providing richer insights into public opinion and perception, supporting product and service personalization, and

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Aspect	Conclusion	Implications
	climate change and e-commerce [14][8][10].	strengthening sentiment-based strategies.
Resource Efficiency Challenges	The high computational resource requirements pose a major challenge, but solutions such as data augmentation and hybrid approaches offer effective alternatives [13][9][15].	Driving innovation to improve cost efficiency, enabling broader access to sentiment analysis for organizations with limited resources.

Table 3 shows that NLP-based transformer models, such as BERT and ELCTRA, provide high accuracy and superior efficiency in cross-language and cross-domain sentiment analysis. Their ability to quickly process unstructured data makes them highly flexible tools, especially in sectors such as finance, education, and healthcare. The main challenge lies in the high computational power requirements, but techniques such as data augmentation and hybrid approaches provide efficient solutions. With their flexibility and consistent performance, these models open up vast opportunities for more accurate and cost-effective global sentiment analysis.

3.2. RQ2: What are the biggest challenges in implementing NLP models for sentiment analysis on real-time data, and how can data streaming techniques overcome these limitations?

The biggest challenges in implementing NLP models for sentiment analysis on real-time data lie in the model's ability to handle large volumes of data, high computing power requirements, and low latency. Real-time data from various platforms, such as social media or customer reviews, is dynamic and unstructured, requiring fast processing without sacrificing accuracy. Transformer-based models like BERT, while superior in accuracy and multilingual capabilities, have operational efficiency limitations in real-time data environments due to their complex computational architecture [6], [10], [13].

To address these limitations, data streaming techniques like Apache Kafka or Apache Flink have been widely adopted. These techniques enable data to be processed incrementally in a continuous stream, reducing model size without significant performance loss. Additionally, the use of GPU-based inference and hybrid approaches, which combine transformers with lexicon-based methods, can enhance analysis efficiency [4], [14], [15]. Overall, the combination of data streaming techniques with model optimization provides a practical solution for addressing the challenges of real-time sentiment analysis, enabling systems to remain responsive without sacrificing accuracy. This approach opens up new opportunities for large-scale applications across various sectors, including business and social surveillance.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

3.3. RQ3: How effective is transfer learning in accelerating NLP model training on domain-specific sentiment datasets without compromising the quality of analysis results?

Transfer learning has proven itself to be a highly efficient approach in accelerating the training of NLP models on domain-specific sentiment datasets without compromising the quality of analysis results. By leveraging pre-trained parameters from models such as BERT, RoBERTa, and GPT, this technique can reduce training time by up to 50-30% compared to training from scratch. For example, CLimateBERT in climate change analysis achieved 92% accuracy with significantly improved training efficiency. These pre-trained models maintain high accuracy, often reaching up to 95%, even on unstructured and domain-specific datasets such as education, healthcare, and finance. Additionally, transfer learning is highly flexible in handling various domains and languages, including those with limited resources like Uyghur and Turkish. In cross-lingual aspect-based analysis, multi-layer models like CNN-BERT demonstrate significant performance improvements, with recall increases of up to 20% compared to traditional methods. Transfer learning is also highly relevant for multimodal data applications, such as combinations of text, images, and audio. In social media and healthcare applications, this approach provides richer insights and better results in understanding public emotions and opinions.

This flexibility makes transfer learning an ideal solution for various challenges in sentiment analysis. This technique not only accelerates model training but also enables adaptation to domains with limited datasets or complex multilingual data. Sectors such as e-commerce, education, social media, and finance can leverage transfer learning capabilities to optimize sentiment analysis at scale while maintaining high efficiency and quality. With time efficiency, consistent accuracy, and adaptability, transfer learning has become the backbone of innovation in modern NLP analysis. Table 4 shows that transfer learning not only improves the training efficiency of NLP models but also keeps the quality of analysis results at a high level. With its flexibility to work on various domains and languages, transfer learning becomes an important solution to address modern challenges in sentiment analysis, both on textual and multimodal data. This approach enables wide applications in sectors such as e-commerce, social media, education, healthcare, and finance, becoming the first choice for complex NLP tasks.

Table 4. Research Results Related to Transfer Learning Efficiency in NLP for Sentiment Analysis

Title	Author	Transfer Learning Results	Key Findings
Climate Change Sentiment	V. S. Anoop et al.	ClimateBERT achieved 92% accuracy	Transfer learning enables rapid adaptation to specific

Title	Author	Transfer Learning Results	Key Findings
Analysis Using Domain Specific Bidirectional Encoder Representations From Transformers		in climate change sentiment analysis with shorter training time.	domains with high accuracy and training efficiency.
AB-LaBSE: Uyghur Sentiment Analysis via the Pre-Training Model with BiLSTM	Y. Pei et al.	LaBSE with BiLSTM uses data augmentation to overcome the limitations of the Uyghur dataset.	Transfer learning maintains accuracy even with a very limited dataset.
An Experimental Analysis of Deep Neural Network-Based Classifiers for Sentiment Analysis Task	M. Shukla and A. Kumar	Transfer learning reduces training time by up to 60% with 90-95% accuracy.	Transfer learning improves training efficiency for domains such as e-commerce and education.
Sentiment Analysis of Students' Feedback with NLP and Deep Learning: A Systematic Mapping Study	Z. Kastrati et al.	BERT achieves high accuracy in sentiment analysis in the education field.	Transfer learning accelerates training for large-scale education data.
An Empirical Evaluation of the Zero-Shot, Few-Shot, and Traditional Fine-Tuning Based Pretrained Language Models for Sentiment Analysis in Software Engineering	M. Shafikuzzaman et al	BERT-based few-shot learning is effective on small datasets with competitive performance.	Transfer learning enables rapid adaptation for small datasets.
Examining Customer Satisfaction Through Transformer-	S. Shan et al.	The Transformer model achieves high accuracy in bilingual sentiment analysis..	Transfer learning understands multilingual context with high efficiency.

Journal of Information Systems and Informatics
Vol. 7, No. 3, September 2025
p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Title	Author	Transfer Learning Results	Key Findings
Based Sentiment Analysis for Improving Bilingual E-Commerce Experiences			
Improving Turkish Text Sentiment Classification Through Task-Specific and Universal Transformations: An Ensemble Data Augmentation Approach	A. Onan and K. F. Balbal	Data augmentation on BERT improves accuracy on Turkish language datasets.	Transfer learning is effective for minority languages with data augmentation.
Optimizing Customer Satisfaction Through Sentiment Analysis: A BERT-Based Machine Learning Approach to Extract Insights	B. Rahman and Maryani	BERT provides optimal results in e-commerce analysis with accuracy >90%.	Transfer learning accelerates analysis without compromising quality.
Affective Knowledge Augmented Interactive Graph Convolutional Network for Chinese-Oriented Aspect-Based Sentiment Analysis	Q. Yang et al	The BERT model with GCN improves accuracy on Chinese and English language datasets.	Transfer learning enables more efficient multilingual analysis.
Multi-Modal Emotion Detection and Sentiment Analysis	S. S. Malik et al	BERT assists multimodal analysis with high accuracy.	Transfer learning leverages multimodal features for deeper analysis.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Title	Author	Transfer Learning Results	Key Findings
Online News-Based Economic Sentiment Index	N. Kang et al	BERT-based economic news analysis achieves high accuracy and provides economic sentiment insights.	Transfer learning accelerates model adaptation on economic datasets.
Low-Resource NLP for Sentiment Analysis	Z. Fang, Y. Liu	Transfer learning addresses data limitations for low-resource languages.	Training efficiency improves with data augmentation.
Real-Time Sentiment Analysis with Optimized Models	K. Lee, T. Zhang	Transfer learning enhances real-time sentiment analysis efficiency with low latency.	Transfer learning enables fast analysis without sacrificing accuracy.
A Multi-Layer Network for Aspect-Based Cross-Lingual Sentiment Classification	K. Sattar et al	Multilingual aspect-based analysis delivers high performance with Transformer models.	Transfer learning supports cross-language processing with efficiency.
Improving Text Representations for Sentiment Analysis	T. Yamamoto, D. Wu	BERT-based text representation improves analysis on unstructured data.	Transfer learning optimizes efficiency and analysis results.
Transformer Models for Financial Sentiment Analysis	L. Zhang, Y. Chen	Transfer learning provides accurate results for public opinion-based financial text.	Accelerates training of financial models with high accuracy..
Analysis of Sentiment Models on E-commerce Reviews	M. Park, J. Seo	BERT-based e-commerce review sentiment analysis provides high accuracy.	Transfer learning accelerates training and analysis results.
Sentiment Analysis in Financial Texts	L. Zhou, W. Wang	BERT provides optimal results for opinion-based financial text.	Transfer learning enables efficient analysis in the financial domain.
Climate-Specific Sentiment Models	H. Ameen, T. Krishnan	BERT for climate change provides high accuracy with rapid adaptation.	Transfer learning accelerates training for specific domains.

Title	Author	Transfer Learning Results	Key Findings
Textual Emotion Detection in Health: Advances and Applications	A.H. Saffar, T.K. Mann, B. Ofoghi	Deep learning-based transfer learning improves emotion detection in healthcare applications with high accuracy.	Effective in processing real-time data for emotion-based health analysis.
Deep Learning and Multilingual Sentiment Analysis on Social Media	M.M. Agüero-Torales, J.I. Abreu Salas, A.G. López-Herrera	Transfer learning supports multilingual sentiment analysis on social media with high efficiency.	Enables analysis on languages with low resources through cross-language data augmentation.
Sentiment Analysis and Opinion Mining on Educational Data: A Survey	T. Shaik, X. Tao, C. Dann, H. Xie, Y. Li, L. Galligan	BERT and GPT models enhance sentiment analysis in educational feedback.	Transfer learning enables faster processing of educational data without sacrificing accuracy.
Recent Advancements and Challenges of NLP-Based Sentiment Analysis	J.R. Jim, M.A.R. Talukder, P. Malakar, M.M. Kabir, K. Nur, M.F. Mridha	Transfer learning based on large models like GPT and BERT leads sentiment analysis across various domains.	Effective for handling multimodal data and improving interpretation in sentiment analysis.
A Multi-Layer Network for Aspect-Based Cross-Lingual Sentiment Classification	K. Sattar, Q. Umer, D.G. Vasbieva, S. Chung, Z. Latif, C. Lee	A multi-layer approach based on CNN-BERT with attention mechanisms improves accuracy on cross-language data.	Transfer learning improves precision, recall, and F1 by up to 23%, 20%, and 22% compared to other approaches.
Sentiment Analysis of Online Reviews: A Machine Learning-Based Approach With TF-IDF Vectorization	N. Sultana et al.	Transfer learning is not explicit, but it is an efficient approach for narrow domains using feature vectorization.	The combination of TF-IDF and SVM achieves 97% accuracy on hotel reviews.
Driving the Technology Value Stream by Analyzing App Reviews	H. Asri et al.	Transfer learning speeds up classification while maintaining high accuracy.	BERT and RoBERTa are used for five-class sentiment classification on Android app reviews.
Big Data Meets Social Networks: A Survey of Analytical	R. Oussous et al.	Although the focus is on surveys, the study emphasizes the value of transfer learning for	It is discussed that the transfer learning approach is important in analyzing

Title	Author	Transfer Learning Results	Key Findings
Strategies and Research Challenges		analytical efficiency in massive data.	large-scale data from social media.
A Comprehensive Survey on AI in Counter-Terrorism and Cybersecurity: Challenges and Ethical Dimensions	N. Ahmad et al.	Transfer learning is positioned as an efficient solution for rapid adaptation and language processing in limited domains.	It raises the challenge of using NLP in sensitive domains such as security.
Exploring the Effects of Personality Traits on Customer Perceived Value	Jiang et al.	It reduces the need for initial training by leveraging hierarchical representation and classification models.	A Doc2Vec-based approach and personality analysis are used to extract sentiment from customer reviews.
Analyzing NLP Techniques to Extract Skill Acquisition Information	Gonzalez-Gomez et al.	Pre-trained models can quickly and accurately extract relevant information.	Transfer learning is used to identify skills through unstructured text.
Enhancing Hajj and Umrah Services Through Social Media Classification	Chelloug et al.	Transfer learning accelerates model adaptation to real-time social data.	NLP-based predictive classification models and swarm intelligence are applied to religious service data.
An Analytical Review of Preprocessing Techniques in Bengali NLP	Chakraborty et al.	Bangla-BERT demonstrates good performance despite resource limitations.	Transfer learning in Bengali shows strong results if preprocessing supports it.
Applied Linguistics With Red-Tailed Hawk Optimizer-Based Ensemble Learning Strategy in Natural Language 34Processing	Hala J. Alshahrani et al.	Transfer learning combined with ensemble strategies and optimization provides high training efficiency.	The combination of CNN, LSTM, and GRU with adaptive optimization produces stable classification.
Pretrained Quantum-Inspired Deep	S. Shi et al.	Improves F1-score by 5.2 points over BERT for WSD and	The QPFE-ERNIE model combines quantum

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Title	Author	Transfer Learning Results	Key Findings
Neural Network for NLP		sentiment classification.	embedding and the ERNIE model.
Challenges and Issues in Sentiment Analysis: A Comprehensive Survey	N. Raghunathan and K. Saravanakumar	DL/TL enables knowledge transfer from a source domain to a target domain, explicitly aiming to improve cross-domain sentiment classification without sacrificing quality.	The key to successful TL is the ability to distinguish between: 1) Pivot Elements (general sentiment words that can be transferred) and 2) Non-Pivot Elements (domain-specific sentiment words). Effective TL uses both for optimal accuracy.
Benchmarking Open-Source Large Language Models for Sentiment and Emotion Classification in Indonesian Tweets	Nasution et al.	LLaMA3 and Gemma2 achieve >90% of ChatGPT's performance in zero-shot settings.	Compare 22 open-source LLMs and ChatGPT-4 on Indonesian data.
Examining Customer Satisfaction Through Transformer-Based Sentiment Analysis for Improving Bilingual E-Commerce Experiences	Shizhong Shan et al.	Transformer performance remains high despite linguistic and translation challenges.	ELECTRA achieves 98.09% accuracy in bilingual e-commerce reviews.
Blockchain-Based Event Detection and Trust Verification Using NLP and Machine Learning	Shahbazi and Byun	Pretrained NLP models facilitate rapid detection of social data.	Combining NLP and blockchain for event trust verification.
An Analytical Analysis of Text Stemming Methodologies in NLP Systems	Jabbar et al.	Transfer learning is effective when combined with strong preprocessing.	Review of over 50 stemming techniques in multilingual NLP.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Title	Author	Transfer Learning Results	Key Findings
Attention in NLP	Galassi et al.	Attention supports transfer learning-based fine-tuning for contextual focus.	Taxonomy of attention models in NLP.
A Cross-Cultural Lingual NLP Analysis of Disability Awareness on Social Media	AIMeraj et al.	Multilingual NLP with transfer learning reveals cultural variations.	Cross-language analysis of Arabic and English discourse on disability.
Advanced Text Summarization Model Incorporating NLP Techniques and Feature-Based Scoring	Kadhim et al.	Pretrained BERT aids in more accurate and faster text summarization.	Combined TF-IDF, Named Entity, and BERTScore models.
The Rise of Artificial Intelligence Phobia: Unveiling News-Driven Spread of AI Fear Sentiment Using ML, NLP, and LLMs	P. Samuel et al.	Pretrained LLMs enable efficient and in-depth emotion classification.	Analysis of 70,000 AI headlines using BERT, LLaMA, and Mistral.
Sentiment Analysis of Twitter Data Using NLP Models: A Comprehensive Review	Aish Albladi et al.	Transfer learning (BERT, RoBERTa) accelerates training and achieves accuracy >90%.	Comprehensive review of NLP models for Twitter data.data Twitter.
Advanced NLP Models for Technical University Information Chatbots: Development and Comparative Analysis	Girija Attigeri et al.	Transfer learning yields significantly better contextual understanding and 46% shorter response times.	Comparative study of chatbots using BERT vs. rule-based systems.
ChatGPT Label: Comparing the	A. H. Nasution and A. Onan.	Transfer learning via LLM can produce	Comparing ChatGPT label accuracy with human

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Title	Author	Transfer Learning Results	Key Findings
Quality of Human-Generated and LLM-Generated Annotations in Low-Resource Language NLP Tasks		human-equivalent annotations.	annotators on low-resource NLP tasks.
Live Event Detection for People's Safety Using NLP and Deep Learning	A.Sen et al.	Transfer learning enables fast and accurate classification of real-time data.	BERT model used to detect real-time events from social text.
Text Mining and Emotion Classification on Monkeypox Twitter Dataset: A Deep Learning-NLP Approach	R. Olusegun et al.	BERT + CNN used to accelerate training while maintaining high sensitivity.	NLP is used for emotion classification during health crises.
Identifying Security and Privacy Violation Rules in Trigger-Action IoT Platforms With NLP Models	M. Baig et al.	Pretrained models accelerate the detection of violation patterns from natural language descriptions.	NLP is used to classify security violations in IoT.
Conspiracy or Not? A Deep Learning Approach to Spot It on Twitter	B. A. Galende et al	The BORJIS model achieved an accuracy improvement of ≥10% compared to other up-to-date techniques in detecting conspiracy and sarcasm—two highly complex and domain-specific sentiment tasks.	Effectiveness in this domain does not only depend on textual features, but also on contextual features/metrics (such as popularity and polarity) that are integrated into the DL architecture to improve the quality of results and information discrimination on Twitter.

3.4. Discussion

The results of this study provide a comprehensive assessment of the current state of NLP-based sentiment analysis using transformer models, specifically focusing on the comparison between transformer-based models and traditional methods, as

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

well as the effectiveness of transfer learning in improving training efficiency and performance. Our findings align with recent research trends, emphasizing the advantages and challenges of using advanced NLP models for sentiment analysis in real-time and domain-specific contexts.

The comparison between transformer-based models such as BERT and traditional approaches, including LSTM and lexicon-based methods, revealed several key insights. First, transformer models consistently outperform traditional methods in terms of accuracy and efficiency, particularly when analyzing multilingual sentiment. As evidenced in the studies analyzed, BERT achieved an accuracy rate of up to 95%, significantly higher than the 80-85% accuracy typical of LSTM and other machine learning models [5], [13]. This is largely due to BERT's ability to capture complex semantic relationships using the attention mechanism, which allows for parallel processing of data, unlike sequential models such as LSTM. Additionally, transformer models demonstrated high flexibility, particularly in multilingual contexts. The models were able to process low-resource languages like Turkish and Uyghur effectively, leveraging data augmentation and fine-tuning strategies [4]. However, despite these advantages, transformer models present resource efficiency challenges. Their computational demands, especially regarding the requirement for GPUs or TPUs, remain a significant barrier for organizations with limited infrastructure. To mitigate this, hybrid approaches combining transformers with traditional methods, such as lexicon-based sentiment analysis, have been proposed. These methods can enhance operational efficiency while maintaining high accuracy, thus making sentiment analysis more accessible for organizations with constrained resources [9].

Real-time sentiment analysis, particularly from dynamic, unstructured data sources like social media and customer reviews, presents unique challenges. The primary issues include the need for high processing speed, the ability to handle large volumes of data, and minimizing latency without sacrificing accuracy. Transformer-based models like BERT, although highly accurate, are not optimized for real-time data processing due to their computational complexity and large model size.

To overcome these challenges, data streaming techniques such as Apache Kafka and Apache Flink are increasingly being adopted. These technologies enable continuous processing of incoming data, reducing the memory footprint and improving latency [6]. Moreover, the combination of transformer models with data streaming techniques helps streamline the sentiment analysis process, allowing for more efficient real-time processing without compromising the quality of results. The integration of GPU-based inference further enhances speed, enabling faster data processing in real-time applications [13]. Additionally, the hybridization of transformer models with traditional lexicon-based methods offers a promising

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

solution to enhance both the efficiency and accuracy of real-time sentiment analysis. This approach allows for the integration of pre-trained models for complex sentiment understanding, while simultaneously incorporating faster, simpler lexicon-based techniques for quicker processing.

Transfer learning has emerged as a key technique in improving the efficiency and performance of NLP models on domain-specific sentiment datasets. Our findings indicate that transfer learning significantly accelerates training time by leveraging pre-trained models such as BERT, RoBERTa, and GPT. This method reduces training time by 30-50% compared to training models from scratch, making it especially useful for domains with limited datasets [13]. For example, in climate change sentiment analysis, the use of ClimateBERT resulted in a 92% accuracy rate, significantly reducing the training time required to adapt the model to the specific domain [15].

Moreover, transfer learning has proven to be highly effective in multilingual and low-resource contexts, as it enables models to generalize across languages with minimal training data. Studies on cross-lingual sentiment analysis, such as those involving Turkish or Uyghur, have demonstrated that transfer learning helps maintain high accuracy even with limited language resources [4]. This adaptability makes transfer learning an ideal solution for real-world sentiment analysis tasks across various domains such as healthcare, e-commerce, and finance, where domain-specific data and languages with limited resources are prevalent. Additionally, the use of data augmentation techniques in conjunction with transfer learning has been shown to further enhance model performance in low-resource environments. By increasing the diversity of the training data, these techniques help improve the generalization capability of transformer models, thus ensuring higher accuracy and robustness when applied to different domains.

The results of this study have several practical implications for both academic research and industrial applications. For academic researchers, the findings underscore the growing importance of transfer learning in sentiment analysis and the need for further investigation into hybrid models that balance computational efficiency and accuracy. The study also highlights the need for domain-specific adaptation, particularly in multilingual contexts and low-resource languages, as well as the integration of real-time processing solutions to enhance the responsiveness of sentiment analysis systems. For industrial applications, the results suggest that organizations can achieve high-quality sentiment analysis by adopting transformer models, particularly BERT and ELECTRA, while addressing the computational resource challenges through hybrid approaches and the use of data streaming techniques. Additionally, transfer learning provides a scalable solution for domain-specific sentiment analysis, allowing companies to implement robust systems with

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

reduced training time, thus facilitating faster deployment and cost-effective solutions.

While the study provides valuable insights, it is not without limitations. One significant challenge is the variability in performance across different domains, which requires more domain-specific customization of models. Additionally, the computational requirements for transformer models remain a substantial barrier for some organizations, and further research is needed to explore more resource-efficient methods. Future research could focus on developing more lightweight transformer models that maintain high performance but require fewer computational resources. Moreover, further exploration into transfer learning for multimodal sentiment analysis, involving the integration of text, images, and audio, could open new avenues for more holistic sentiment understanding, particularly in complex domains like healthcare and social media.

4. CONCLUSION

This study confirms that transfer learning is one of the most effective approaches in Natural Language Processing (NLP) for sentiment analysis, especially compared to traditional methods. Pre-trained models such as BERT, RoBERTa, and GPT have been shown to reduce training time by 50–70% while maintaining high accuracy above 95%, even in complex domains like e-commerce, healthcare, education, and finance. In multilingual scenarios with limited resources, such as Turkish and Uyghur, strategies like cross-cultural data augmentation and zero-shot learning have significantly improved performance. Furthermore, cross-lingual aspect-based analysis shows that the CNN-BERT combination can improve accuracy, recall, and F1-score, while multimodal applications (text, image, audio) enrich analytical insights, particularly in social media and healthcare. Despite consistently delivering superior results, significant challenges still arise from computational power requirements. Large models like GPT require advanced infrastructure (GPU/TPU) which is often beyond the reach of small organizations or industries with limited resources. This creates a real-world implementation gap. In response, hybrid approaches—for example, combining transformer models with lexicon-based methods—emerge as promising practical solutions because they can reduce computational load without sacrificing accuracy. However, their implementation still requires more in-depth research to evaluate performance consistency across various domains.

In line with the research questions, three main conclusions can be drawn. First, NLP-based transformer models have proven superior to traditional approaches in terms of accuracy and efficiency (RQ1). Second, real-time data application faces significant challenges in terms of latency and computation, although streaming techniques and hybrid optimization are beginning to show potential solutions

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

(RQ2). Third, transfer learning methods effectively accelerate the training process by up to 70% on domain-specific datasets, while maintaining analysis quality (RQ3). For future research directions, several steps need to be prioritized. First, the exploration of lightweight models that can run on mobile devices and resource-constrained environments. Second, improving interpretability to make models more transparent and acceptable in sensitive sectors such as finance and healthcare. Third, the development of model compression and distillation strategies that not only reduce computational needs but also consider sustainability, including reducing the carbon footprint of the training process. Thus, transfer learning not only addresses efficiency challenges in sentiment analysis but also opens the way for innovation in various domains and languages, making it a crucial pillar in natural language processing in the modern data era.

REFERENCES

[1] Y. Lin and T. Liu, "Enhanced Transformer-BLSTM Model for Classifying Sentiment of User Comments on Movies and Books," *IEEE Access*, vol. 12, pp. 88634–88641, 2024, doi: 10.1109/ACCESS.2024.3416755.

[2] H. Shim, D. Lowet, S. Luca, and B. Vanrumste, "LETS: A Label-Efficient Training Scheme for Aspect-Based Sentiment Analysis by Using a Pre-Trained Language Model," *IEEE Access*, vol. 9, pp. 115563–115578, 2021, doi: 10.1109/ACCESS.2021.3101867.

[3] S. Shan, J. Sun, and R. M. C. Macawile, "Examining Customer Satisfaction Through Transformer-Based Sentiment Analysis for Improving Bilingual E-Commerce Experiences," *IEEE Access*, vol. 13, pp. 51027–51041, 2025, doi: 10.1109/ACCESS.2025.3551666.

[4] A. Onan and K. F. Balbal, "Improving Turkish Text Sentiment Classification Through Task-Specific and Universal Transformations: An Ensemble Data Augmentation Approach," *IEEE Access*, vol. 12, pp. 4413–4458, 2024, doi: 10.1109/ACCESS.2024.3349971.

[5] B. Rahman and Maryani, "Optimizing Customer Satisfaction Through Sentiment Analysis: A BERT-Based Machine Learning Approach to Extract Insights," *IEEE Access*, vol. 12, pp. 151476–151489, 2024, doi: 10.1109/ACCESS.2024.3478835.

[6] N. J. Prottasha *et al.*, "Transfer Learning for Sentiment Analysis Using BERT Based Supervised Fine-Tuning," *Sensors*, vol. 22, no. 11, Jun. 2022, doi: 10.3390/s22114157.

[7] M. Shafikuzzaman, M. R. Islam, A. C. Rolli, S. Akhter, and N. Seliya, "An Empirical Evaluation of the Zero-Shot, Few-Shot, and Traditional Fine-Tuning Based Pretrained Language Models for Sentiment Analysis in Software Engineering," *IEEE Access*, vol. 12, pp. 109714–109734, 2024, doi: 10.1109/ACCESS.2024.3439450.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[8] V. S. Anoop, T. K. A. Krishnan, A. Daud, A. Banjar, and A. Bukhari, "Climate Change Sentiment Analysis Using Domain Specific Bidirectional Encoder Representations from Transformers," *IEEE Access*, vol. 12, pp. 114912–114922, 2024, doi: 10.1109/ACCESS.2024.3441310.

[9] M. Rizinski, H. Peshov, K. Mishev, M. Jovanovik, and D. Trajanov, "Sentiment Analysis in Finance: From Transformers Back to eXplainable Lexicons (XLex)," *IEEE Access*, vol. 12, pp. 7170–7198, 2024, doi: 10.1109/ACCESS.2024.3349970.

[10] Q. Yang, Z. Kadeer, W. Gu, W. Sun, and A. Wumaier, "Affective Knowledge Augmented Interactive Graph Convolutional Network for Chinese-Oriented Aspect-Based Sentiment Analysis," *IEEE Access*, vol. 10, pp. 130686–130698, 2022, doi: 10.1109/ACCESS.2022.3228299.

[11] M. M. Agüero-Torales, J. I. Abreu Salas, and A. G. López-Herrera, "Deep learning and multilingual sentiment analysis on social media data: An overview," *Appl Soft Comput*, vol. 107, Aug. 2021, doi: 10.1016/j.asoc.2021.107373.

[12] J. R. Jim, M. A. R. Talukder, P. Malakar, M. M. Kabir, K. Nur, and M. F. Mridha, "Recent advancements and challenges of NLP-based sentiment analysis: A state-of-the-art review," *Natural Language Processing Journal*, vol. 6, p. 100059, Mar. 2024, doi: 10.1016/j.nlp.2024.100059.

[13] C. H. P. Panjaitan, "Systematic Literature Review of Sentiment Analysis on Various Review Platforms in the Tourism Sector," *Journal of Advanced Computer Knowledge and Algorithms*, vol. 2, no. 1, pp. 12-18, 2025.

[14] S. S. Malik *et al.*, "Multi-Modal Emotion Detection and Sentiment Analysis," *IEEE Access*, vol. 13, pp. 59790–59810, 2025, doi: 10.1109/ACCESS.2025.3552475.

[15] Y. Pei, S. Chen, Z. Ke, W. Silamu, and Q. Guo, "AB-LaBSE: Uyghur Sentiment Analysis via the Pre-Training Model with BiLSTM," *Applied Sciences (Switzerland)*, vol. 12, no. 3, Feb. 2022, doi: 10.3390/app12031182.

[16] K. Sattar, Q. Umer, D. G. Vasbieva, S. Chung, Z. Latif, and C. Lee, "A multi-layer network for aspect-based cross-lingual sentiment classification," *IEEE Access*, vol. 9, pp. 133961–133973, 2021, doi: 10.1109/ACCESS.2021.3116053.

[17] A. H. Saffar et al., "Textual Emotion Detection in Health: Advances and Applications," J. Biomed. Inform., vol. 137, p. 104258, Jan. 2023, doi: 10.1016/j.jbi.2022.104258.

[18] T. Shaik et al., "Sentiment Analysis and Opinion Mining on Educational Data: A Survey," Nat. Lang. Process. J., vol. 2, p. 100003, Mar. 2023, doi: 10.1016/j.nlp.2022.100003.

[19] Y. S. Mehanna and M. B. Mahmuddin, "A Semantic Conceptualization Using Tagged Bag-of-Concepts for Sentiment Analysis," IEEE Access, vol. 9, pp. 118736–118756, 2021, doi: 10.1109/ACCESS.2021.3107237.

[20] M. Shukla and A. Kumar, "An Experimental Analysis of Deep Neural Network Based Classifiers for Sentiment Analysis Task," IEEE Access, vol. 11, pp. 36929–36944, 2023, doi: 10.1109/ACCESS.2023.3266640.
[21] Z. Kastrati et al., "Sentiment Analysis of Students' Feedback with NLP and Deep Learning: A Systematic Mapping Study," Appl. Sci., vol. 11, no. 9, p. 3986, Apr. 2021, doi: 10.3390/app11093986.
[22] H. Saleh et al., "Enhanced Arabic Sentiment Analysis Using a Novel Stacking Ensemble of Hybrid and Deep Learning Models," Appl. Sci., vol. 12, no. 18, p. 8967, Sep. 2022, doi: 10.3390/app12188967.
[23] F. Husain et al., "Bridging the Kuwaiti Dialect Gap in Natural Language Processing," IEEE Access, vol. 12, pp. 27709–27722, 2024, doi: 10.1109/ACCESS.2024.3364367.
[24] S. Kim et al., "Understanding Mental Health Issues in Different Subdomains of Social Networking Services: Computational Analysis of Text-Based Reddit Posts," J. Med. Internet Res., vol. 25, no. 1, p. e49074, Nov. 2023, doi: 10.2196/49074.
[25] N. Kang et al., "Online News-Based Economic Sentiment Index," IEEE Trans. Big Data, vol. 11, no. 3, pp. 1464–1474, Jun. 2025, doi: 10.1109/TBDATA.2024.3474211.
[26] K. Alemerien et al., "Sentiment Analysis of Online Reviews: A Machine Learning Based Approach with TF-IDF Vectorization," J. Mobile Multimedia, pp. 1089–1116, Dec. 2024, doi: 10.13052/jmm1550-4646.2055.
[27] S. Das et al., "Driving the Technology Value Stream by Analyzing App Reviews," IEEE Trans. Softw. Eng., vol. 49, no. 7, pp. 3753–3770, Jul. 2023, doi: 10.1109/TSE.2023.3270708.
[28] S. S. Singh et al., "Big Data Meets Social Networks: A Survey of Analytical Strategies and Research Challenges," IEEE Access, vol. 13, pp. 98668–98698, 2025, doi: 10.1109/ACCESS.2025.3576143.
[29] I. Syllaidopoulos et al., "A Comprehensive Survey on AI in Counter-Terrorism and Cybersecurity: Challenges and Ethical Dimensions," IEEE Access, vol. 13, pp. 91740–91764, 2025, doi: 10.1109/ACCESS.2025.3572348.
[30] Z. Jiang et al., "Exploring the Effects of Personality Traits on Customer Perceived Value Based on Text Decomposition," IEEE Access, vol. 13, pp. 62137–62153, 2025, doi: 10.1109/ACCESS.2025.3558374.
[31] L. J. Gonzalez-Gomez et al., "Analyzing Natural Language Processing Techniques to Extract Meaningful Information on Skills Acquisition From Textual Content," IEEE Access, vol. 12, pp. 139742–139757, 2024, doi: 10.1109/ACCESS.2024.3465409.
[32] S. A. Chelloug et al., "Enhancing Hajj and Umrah Services Through Predictive Social Media Classification," IEEE Access, vol. 13, pp. 67220–67238, 2025, doi: 10.1109/ACCESS.2025.3559204.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[33] S. Chakraborty et al., "An Analytical Review of Preprocessing Techniques in Bengali Natural Language Processing," IEEE Access, vol. 13, pp. 112428–112445, 2025, doi: 10.1109/ACCESS.2025.3574234.
[34] H. J. Alshahrani et al., "Applied Linguistics With Red-Tailed Hawk Optimizer-Based Ensemble Learning Strategy in Natural Language Processing," IEEE Access, vol. 11, pp. 132448–132456, 2023, doi: 10.1109/ACCESS.2023.3331061.
[35] J. Shi et al., "Pretrained Quantum-Inspired Deep Neural Network for Natural Language Processing," IEEE Transactions on Cybernetics, vol. 54, no. 10, pp. 5973–5985, Oct. 2024, doi: 10.1109/TCYB.2024.3398692.
[36] T. Fontes et al., "Leveraging Social Media as a Source of Mobility Intelligence: An NLP-Based Approach," IEEE Open Journal of Intelligent Transportation Systems, vol. 4, pp. 663–681, 2023, doi: 10.1109/OJITS.2023.3308210.
[37] A. H. Nasution et al., "Benchmarking Open-Source Large Language Models for Sentiment and Emotion Classification in Indonesian Tweets," IEEE Access, vol. 13, pp. 94009–94025, 2025, doi: 10.1109/ACCESS.2025.3574629.
[38] N. Raghunathan and K. Saravanakumar, "Challenges and Issues in Sentiment Analysis: A Comprehensive Survey," *IEEE Access*, vol. 11, pp. 69626–69642, 2023, doi: 10.1109/ACCESS.2023.3293041.
[39] Z. Shahbazi and Y.-C. Byun, "Blockchain-Based Event Detection and Trust Verification Using Natural Language Processing and Machine Learning," IEEE Access, vol. 10, pp. 5790–5800, 2022, doi: 10.1109/ACCESS.2021.3139586.
[40] A. Jabbar, et al., "An Analytical Analysis of Text Stemming Methodologies in Information Retrieval and Natural Language Processing Systems," IEEE Access, vol. 11, pp. 133681–133702, 2023, doi: 10.1109/ACCESS.2023.3332710.
[41] A. Galassi, et al., "Attention in Natural Language Processing," IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 10, pp. 4291–4308, Oct. 2021, doi: 10.1109/TNNLS.2020.3019893.
[42] Z. Almeraj, et al., "A Cross-Cultural/Lingual Natural Language Processing Analysis of Disability Awareness on Social Media," *IEEE Access*, vol. 13, pp. 110128–110150, 2025, doi: 10.1109/ACCESS.2025.3580608.
[43] E. A. Kadhim, et al., "Advanced Text Summarization Model Incorporating NLP Techniques and Feature-Based Scoring," IEEE Access, vol. 13, pp. 19302–19319, 2025, doi: 10.1109/ACCESS.2025.3528830.
[44] J. Samuel, et al., "The Rise of Artificial Intelligence Phobia! Unveiling News-Driven Spread of AI Fear Sentiment Using ML, NLP, and LLMs," IEEE Access, vol. 13, pp. 125944–125969, 2025, doi: 10.1109/ACCESS.2025.3588179.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[45] A. Albladi, et al., "Sentiment Analysis of Twitter Data Using NLP Models: A Comprehensive Review," IEEE Access, vol. 13, pp. 30444–30468, 2025, doi: 10.1109/ACCESS.2025.3541494.

[46] G. Attigeri, et al., "Advanced NLP Models for Technical University Information Chatbots: Development and Comparative Analysis," IEEE Access, vol. 12, pp. 29633–29647, 2024, doi: 10.1109/ACCESS.2024.3368382.

[47] A. H. Nasution and A. Onan, "ChatGPT Label: Comparing the Quality of Human-Generated and LLM-Generated Annotations in Low-Resource Language NLP Tasks," IEEE Access, vol. 12, pp. 71876–718900, 2024, doi: 10.1109/ACCESS.2024.3402809.

[48] A. Sen et al., "Live Event Detection for People's Safety Using NLP and Deep Learning," IEEE Access, vol. 12, pp. 6455–6472, 2024, doi: 10.1109/ACCESS.2023.3349097.

[49] R. Olusegun et al., "Text Mining and Emotion Classification on Monkeypox Twitter Dataset: A Deep Learning-Natural Language Processing (NLP) Approach," IEEE Access, vol. 11, pp. 49882–49894, 2023, doi: 10.1109/ACCESS.2023.3277868.

[50] B. Breve et al., "Identifying Security and Privacy Violation Rules in Trigger-Action IoT Platforms With NLP Models," IEEE Internet of Things Journal, vol. 10, no. 6, pp. 5607–5622, Mar. 2023, doi: 10.1109/JIOT.2022.3222615.

[51] B. A. Galende *et al.*, "Conspiracy or Not? A Deep Learning Approach to Spot It on Twitter," *IEEE Access*, vol. 10, pp. 38370–38378, 2022, doi: 10.1109/ACCESS.2022.3165226.