Indian Journal of Information Sources and Services
ISSN: 2231-6094 (P) Vol.15, No.4, 2025, pp.383-392

DOI: https://doi.org/10.51983/ijiss-2025.IJISS.15.4.43

AI-Enabled Sentiment Analysis for Strategic Content Curation

Nigora Bo'tayeva[1*], Gulnora Mirazimova[2], Dr.C. Rajan[3], Haider Mohammed Abbas[4], Akmaljon Abdullaev[5], Samida Mustafaeva[6] and Ravshan Khomitov[7]

[1*]Senior Lecturer, Department of Theory and Methodology of Primary Education, Jizzakh State Pedagogical University, Uzbekistan
[2]Department of Telecommunication Engineering, Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Tashkent, Uzbekistan
[3]Professor, Department of CSE(AIML), K.S. Rangasamy College of Technology, Tiruchengode, India
[4]Department of Computers Techniques Engineering, College of Technical Engineering, The Islamic University, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, The Islamic University of Al Diwaniyah, Al Diwaniyah, Iraq
[5]Department of Information Technology, Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" National Research University, Tashkent, Uzbekistan; Peter the Great St. Petersburg Polytechnic University, Saint Petersburg, Russia
[6]Tashkent State University of Oriental Studies, Tashkent, Uzbekistan
[7]National University of Uzbekistan named after Mirzo Ulugbek, Toshkent, Uzbekistan
E-mail: [1]a.butayev.048@gmail.com, [2]gmirazimova1974@gmail.com, [3]rajan@ksrct.ac.in, [4]eng.iu.comp.haideralabdeli@gmail.com, [5]a.abdullayev@tiiame.uz, [6]samida_mustafayeva@tsuos.uz, [7]xamitovravshan7@gmail.com
ORCID: [1]https://orcid.org/0009-0009-8136-9179, [2]https://orcid.org/0009-0006-4313-4086, [3]https://orcid.org/0000-0002-7834-8563, [4]https://orcid.org/0009-0005-1464-7678, [5]https://orcid.org/0000-0002-8983-3898, [6]https://orcid.org/0009-0008-3067-5275, [7]https://orcid.org/0000-0003-2184-7852

(Received 10 September 2025; Revised 22 October 2025, Accepted 10 November 2025; Available online 15 December 2025)

Abstract - **The following paper presents a content curation sentiment detection model based on AI, and why it is crucial to protect the user data during the analysis. The model employs the existing technologies of natural language processing (NLP) and machine learning to analyze the content that is created by users during a social media post, review, and comment. The model classifies sentiments as positive, neutral, and negative and proposes individual content suggestions depending on the created users' interests. In addition, the model has implemented data protection policies which include data encryption, role-based access control (RBAC), as well as safe data scraping APIs to access the social media and review sites. Such data protection policies will guarantee privacy and integrity of user data and hence reduce the possibilities of unauthorized access, breach, and exploitation. The ability of the model to be adjusted to the evolving feelings of the users, together with the security measures, will provide a secure and ethical alternative to content curation. The results of the pilot research indicate that there is an indication of a large positive effect of the sentiment-analysis attention-based system on both engagement and post-content engagement outcomes. This paper will discuss the affordances of AI as a means of developing responsive, user-friendly content to be used in the work of a curator by designing AI security, privacy, and personalization of the content. Findings offer proof of the worth of secure systems installed to prevent adversarial assaults and information manipulation to make a safe, dependable system application of AI in content aggregation.**

Keywords: **Artificial Intelligence, Sentiment Analysis, Data Privacy, AI Security, Secure Content Curation, User Engagement, Machine Learning, Natural Language Processing (NLP), Content Curation**

I. INTRODUCTION

1.1 Definition of AI-Enabled Sentiment Analysis

The term AI-enabled sentiment analysis describes the use of artificial intelligence to automate the process of detecting and categorizing the emotive content and subjective content of textual data, using the concepts and techniques related to natural language processing (NLP) and machine learning (ML). Sentiment analysis enables a system to assess emotion as positive, negative, or neutral regarding a user-generated source, such as social media posts, product reviews, or news articles (Liu, 2020). AI models that assess text to acquire elementary sentiments, more complex emotions, or contextual indicators are representative of a wide range of public opinion and user activity (Rahman, et al 2025; Li & Huang, 2024). Sentiment analysis methods have typically used lexicons or rule-based approaches. The introduction of artificial intelligence during the twenty-first century changed the traditional methods of conduct as models can learn from large datasets and produce predictions with limited or no human interference (Huang, 2024; Harris, et al 2024). Past experiences proved that the development of accuracy and interpretability with tasks in sentiment analysis immensely benefited from modern deep learning architecture, as recurrent neural networks (RNNs), Bidirectional Encoder Representations from Transformers (BERT), and attention mechanisms (Gajula,2025; Akshayaa Raaja Shri et al., 2022). These systems can ow process data in almost any language, identify sarcasm, and explore sentiment across a vast number of platforms.

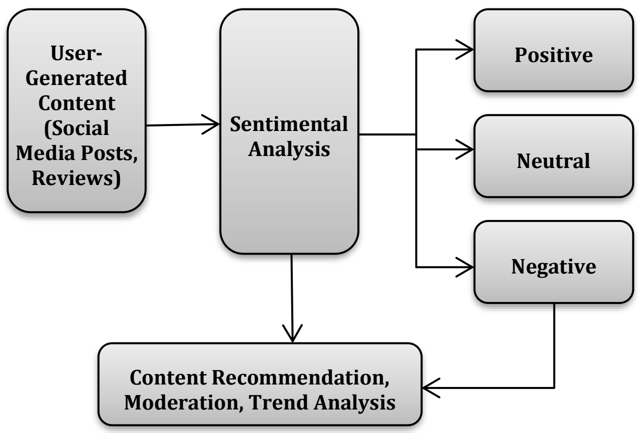

Fig. 1(a) Conceptual Overview of AI-Enabled Sentiment Analysis in Content Curation

According to Fig. 1(a), AI is applied in sentiment analysis in content curation. It begins with inputs in the form of constituents, i.e., social media posts and reviews, which are run through an AI model sentiment analysis engine. The sentiment analysis AI engine analyzes the data and classifies its content into positive, neutral, or negative sentiments. Sentiment analysis can assist in the facilitation of advanced content personalization, holistic user-centered content recommendation, and, possibly, automated moderation of content, or real-time evaluation of trends, which enhance the relevance, safety, and strategic benefits of tracking curated content.

However, since the AI systems that perform sentiment analysis are the heart of the content curation process, which relies on the user emotion, it appears that user emotion can be viewed as not resistant to the largest potential adversarial attacks and manipulation. Algorithms of sentiment analysis might also be adversarially attacked, in which the adversary introduces small perturbations in the input data; the modified data may succeed in deceiving the AI systems to make inaccurate insights using the AI input data analysis. Moreover, the emotion of the data may be usurped, or offset, so as to be able to debate or influence the rural mass opinion, or to capitalize upon the sentiment or emotion or psychological condition of the user and obtain a desired disinformation effect, or manipulate the user into a psychological state of being. These vulnerabilities indicate the significance that the sentiment analysis framework itself carries a strong threat model, is purposefully safe, trustworthy, and is thought of as an abuse-resistant system.

1.2 Importance of Sentiment Analysis in Curation of Content

It is quite crucial that the security be enhanced to ensure that sensitive user information is not lost, though sentiment analysis is one of the core components of content curation. This involves encrypting data when at rest and in transit, controlling access to information data by authorized users using role-based access control (RBAC), and applying secure APIs to aggregate and/or extract information on social media sites and review sites. Such a security level will safeguard not only the data of the user and their right to privacy, but will also keep the sentiment analysis models based on artificial intelligence in a secure and safe environment, and not be abused and exploited.

Speaking more generally, content curation is merely sorting, organizing, and presenting information to cater to the interests of the audience. The trends of emotion and tone-based content personalization are becoming a necessity in the technology era within the educational, marketing, and media fields (Chakraborty et al., 2020; Gowindasamy, 2018). This further increases the level of uniformity and emotion on the user side, and through this, curators can personalize content through sentiment analysis. Emotion-driven content curation has improved AI-enabled sentiment analysis by enabling users to use emotion and improve the layout of their content in real-time. As an illustration, studying the sentiments of social media could assist marketers in determining the trending topics and optimizing their advertisements (Zhang et al., 2022; Hakimov et al., 2024). In the same way, news sources and content platforms use sentiment scores to suggest articles that resonate with the emotional feelings of the readers and increase engagement and retention (Medhat et al., 2014; Bosco et al., 2023).

Brand management also involves the understanding of sentiment so that it can quickly respond to the perception of the masses and counter the negative brand images (Thelwall, 2016; Mahdavipur & Ghermezi, 2018). Sentimental analysis combined with AI can detect and mark fraudulent or deceptive texts and emotionally manipulative stories, which improves the validity and final quality of provided information (Khan et al., 2021; Etuk et al., 2024). This creates a more regulatory, user-friendly content ecosystem.

Nonetheless, although sentiment analysis is essential in the delivery of content depending on the emotional preferences of the users, it entails handling extensive amounts of sensitive user-generated data, which is highly problematic with respect to privacy and data security. The platforms should be reliable to guarantee the security of user information, especially when generating sentiment. In this research, we take into account the privacy of sentiment information and suggest security measures to safeguard the users' information throughout the sentiment analysis. We also comment on how our AI-powered content curation model can be applied in secure systems, where the content is not only secure but also the data is protected, and the dynamically customized content can be altered in real-time according to the sentiment analysis without compromising user privacy and security.

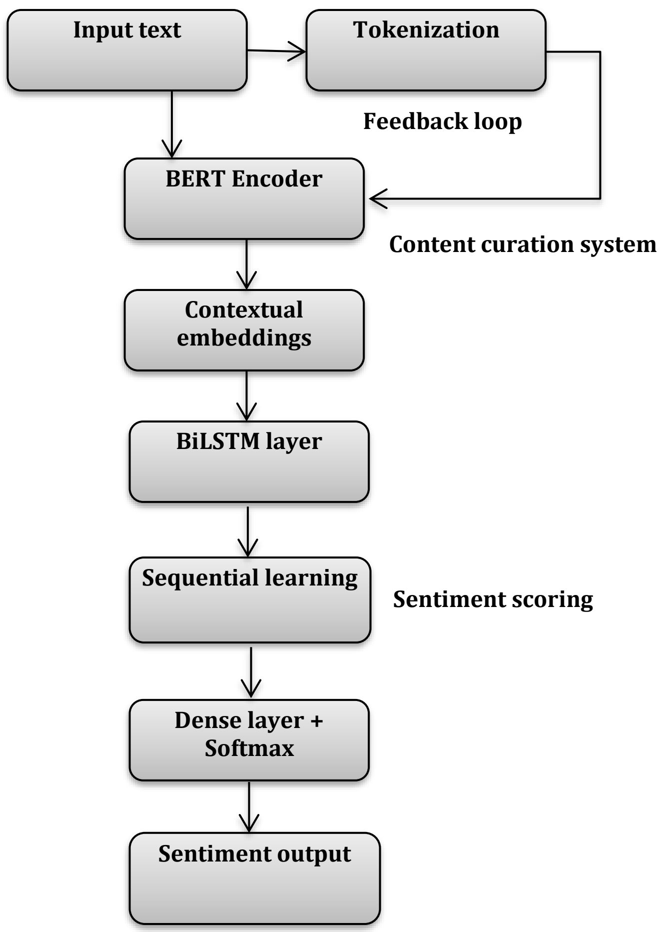

Fig. 1(b) Proposed BiLSTM–BERT Sentiment Analysis Framework

BiLSTM–BERT Sentiment Analysis Framework aims to classify sentiments in text using cutting-edge natural language processing techniques. Sentiment analysis always starts with text input, which is then divided into smaller workable units referred to as tokens. They are fed into a BERT encoder, which creates embeddings that show the context and meaning of the words in the language. Contextual embeddings are passed to a Bidirectional Long Short-Term Memory (BiLSTM) layer where sequential learning takes place using past and future information. Information from BiLSTM is output through a dense layer and a softmax activation function to classify sentiments. Other than the main one mentioned above, the architecture also has optional features like a feedback loop for model fine-tuning and a content curation system for improving adaptive learning and response accuracy, as shown in Fig. 1(b).

1.3 Purpose of the Research Paper

This research paper focuses on designing and assessing an AI-enabled sentiment analysis framework for strategic content curation. It aims to explore the potential of utilizing sophisticated sentiment analysis algorithms to tailor digital content presentations to users' emotions and behavioral trends. This study aims to apply various AI methods, data workflows, and performance evaluation techniques to sentiment extraction and real-time content adaptation. The paper aims to validate, through empirical research and analysis, the effectiveness of the model in enhancing user engagement and personalizing content. Additionally, the study aims to develop a rationale and methodological framework for integrating sentiment-aware technologies into digital systems, highlighting their applications in marketing, education, journalism, and entertainment. In doing so, the study contributes to the development of intelligent content systems and enhances the responsiveness of digital technologies to human emotions (Pang & Lee, 2008; Feldman, 2013).

The document consists of six chapters. Following this introduction, a review of the literature on techniques for sentiment analysis, previous AI implementations, and the relevance of content curation is presented in Section II. This is followed by a discussion of the methodology, which includes data collection, model design, and assessment standards in Section III. Comparative analysis and performance evaluation are discussed in Section IV. The analysis of results in Section V is accompanied by an explanation of the results, outlining the noted constraints, and providing actionable guidance for further inquiry into the theoretical and practical dimensions of the study. In the final section, we summarize the most impactful conclusions of the study along with opposed directions for investigation in AI-based sentiment analysis focused on strategic content curation aimed at future development.

II. Literature Review

Sentiment analysis, often referred to as opinion mining, is a natural language processing (NLP) system theory that seeks to identify sentiments in text and classify them as positive, negative, or neutral (Alhumoud, et al 2022; Dorofte & Krein, 2024). Three techniques can be identified in sentiment analysis: lexicon-based approaches, machine learning methods, and hybrid techniques. Based on a sentiment-bearing lexicon and a set of words belonging to certain classes with scores, lexicon-based approaches are constructed. These approaches are simple and without a doubt easy to follow; however, they are contextually blind. Improved performances have been experienced with the use of some classifying machines, which include Naïve Bayes, Support Vector Machines (SVM), and decision trees, all of which learn from provided labelled content (Pang et al., 2002; Saxena, 2024). Recently, more advanced models such as Convolutional Neural Networks (CNN), long short-term memory (LSTM) networks, and BERT model transformers have deepened the capabilities of performing sophisticated linguistic feature identification. With incorporated domain understanding, (Araque et al., 2017) argue that hybrid techniques offer superior intelligence, comparable to that of data-driven models, in addition to more optimal contextual comprehension, thereby outclassing rule-based models. These models outperform others in real-time applications and perform intricate sentiment analysis.

Many researchers have explored how artificial intelligence can enhance sentiment analysis. (Socher et al., 2013) developed a recursive deep learning model that enhances sentiment detection in complex texts, such as movie reviews, by taking into account the syntactic structure of sentences. Along similar lines, the use of BERT in sentiment classification showed that transformer-based models outperform traditional models in sentiment extraction, where context is crucial for understanding. Analysis of sentiment within a particular domain also achieved great results. For instance, (Al-Smadi et al., 2017) reviewed the field of Arabic sentiment analysis and showcased the need to translate culture and language into AI models (Rojas & García, 2024; Moretti & Tanaka, 2025). Similarly, reviewed and analyzed product reviews and constructed deep neural networks for understanding implications of customer insights on product design and marketing. An emerging trend is multimodal sentiment analysis that includes text, audio, and motion pictures. (Poria et al., 2017) addressed the application of multimodal fusion strategies toward accurate sentiment detection on social media. This extends the scope of AI-enabled sentiment analysis beyond text, including video phones and other real-time communications environments.

Sentiment analysis has become increasingly applicable in content curation across various industries, including marketing, media, education, and public relations. In marketing, companies utilize sentiment-aware systems to assist brands in crafting, messaging, and responding to customers in real-time (Ghiassi et al., 2013; Rao & Menon, 2024). Netflix and YouTube apply sentiment analysis to improve their recommendation systems to match user content suggestions with their emotional responses and preferences. In journalism, sentiment analysis is applied in selection processes to filter news content that targets readers emotionally. (Lee & Choi, 2020) discovered that news aggregators that employed sentiment filtering had improved user engagement. To boost motivation and learning outcomes, educational platforms are modifying content based on students' emotions using sentiment analysis. Besides education, sentiment analysis is applied in public relations and corporate communications to gauge public sentiment on brands, which reveals chances for early response and adjustment of messages when issues start emerging (Jiang et al., 2021; Devi & Priya, 2024; Luo et al., 2022; Al-Smadi et al., 2017). Such an application of sentiment analysis maximizes reputation management and audience engagement. Overall, sentiment analysis helps digital platforms adjust content based on users' emotions, enhancing user experience, loyalty, and engagement in a data-rich environment.

III. METHODOLOGY

In this study, a BiLSTM-BERT hybrid model is used to classify user-generated content as positive, neutral, or negative sentiment. However, maintaining the integrity and security of user-generated content throughout analysis is critical. In response to these challenges, the framework incorporates a number of security-related frameworks and methodologies. User-created content is collected using secured APIs from a variety of platforms (e.g., Twitter, Reddit, product reviews), secured via HTTPS encryption for secure transmission, then encrypted via AES to prevent unauthorized access to securely stored data, and then defense mechanisms are employed to ensure enhanced data security and privacy. Anonymization is also accomplished by complicated statistical data processes that delete personally identifiable information (PII) during the data analysis process and replace it with pseudonyms to enhance data privacy during the data analysis. The APIs used to scrape user-created data are secured via OAuth protocols or secured with tokens, and only authenticated queries will be permitted access to the data collection. Adversarial defense measures to thwart adversarial attacks, which intrinsically characterize adversarial attacks as a scenario where small changes are made to input data and mislead sentiment analysis models. The model is taught to be defense-aware of adversarial training to withstand resistance from minor input data changes. The BiLSTM-BERT model is trained using tokenized and pre-processed text data at each step of the data analysis strategy (e.g., data collection, input data, preprocessing, model methods) to take into consideration the security aspects while assuring higher accuracy during the sentiment classification and protecting the user's data while processing it. Lastly, below is the pseudocode of the method of executing the sentiment analysis process, including the security-based aspects and adversarial defence.

3.1 Detailing the Procedures of Data Collection

This research's data was acquired from many distinct websites, including Twitter and Reddit, review websites, and comment sections of a variety of news articles. Data collection was done via APIs, which allowed for both live streaming and scraping of historical data from posts made with particular hashtags and keywords associated with entertainment, politics, technology, etc. In an effort to streamline the data for quality, some preprocessing was done. This included deduplication, cleaning of irrelevant spam content, and standard text cleaning procedures that involved changing text to lowercase, removing punctuation, and deleting stopwords. In addition, the data underwent tokenization and stemming. Moreover, each text was timestamped and labeled with the source, which aided in analysis and segmentation during the content curation phase. In order to mitigate any bias in the model during training, a balanced dataset containing all categories of sentiment (positive, negative, neutral) was maintained throughout the procedure. All categories were sufficiently represented when the dataset was divided using stratified sampling into 70% for training and 15% each for validation and testing.

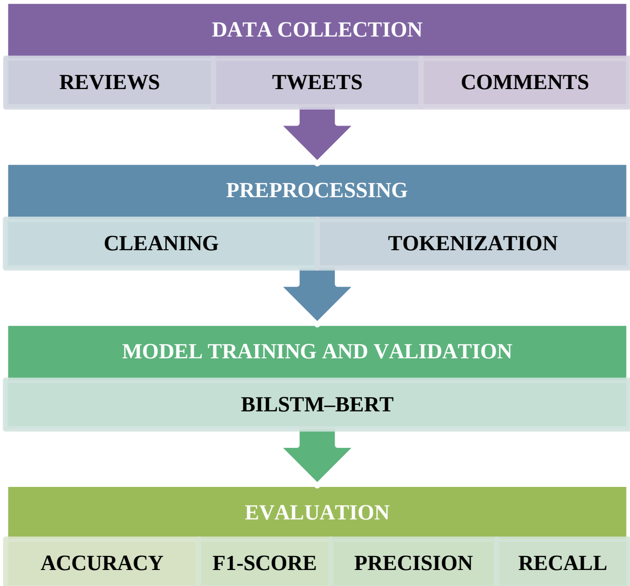

Fig. 2 Data Flow and Processing Pipeline for AI-Enabled Sentiment Analysis

Fig. 2 demonstrates the entire data flow pipeline for the AI-enabled sentiment analysis for targeted content curation. Initially, textual content is sourced from multiple platforms, including reviews, tweets, and comments. The raw data undergoes a sequence of preprocessing steps, which include data cleaning, tokenization, and all required transformations prior to feeding the model, culminating in the removal of noise and organization into analyzable units. The deep learning models are trained and fine-tuned in a dedicated model training phase, after which the model is subjected to validation testing using a holdout data set to evaluate generalizability. Finally, the model undergoes performance evaluation through various quantitative measurement techniques, including, but not limited to, accuracy and F1-score, to ascertain its effectiveness in classifying sentiment categories. This process enables the creation of interpretable and scalable sentiment systems that are tactically optimized during the process of content curation.

3.2 Explanation of the AI-Based Approaches Used for Sentiment Analysis

The analysis of sentiment is conducted using a sentiment analysis model based on the circuit institutions of deep learning frameworks with RNNs and transformers processed within it. In the first step, sequential order dependencies found in the text are captured by BiLSTM networks. BiLSTMs allow for the understanding of sentiment analysis coming from previous and subsequent words in a phrase being discussed in a statement. A BiLSTM that emits an output will undergo a feeding process to a transformer layer, such as BERT - Bidirectional Encoder Representations from Transformers, which is well known for outputting contextualized embedding outputs. The nature of these embeddings is contextual and provides a greater understanding of the particular words, while also developing a complete understanding of deeper meanings.

Mathematically, the sentence above can be expressed in terms of a sequence of word embeddings $X = [x_1, x_2, \ldots, x_n]$. In a recurrent neural network (RNN), a BiLSTM is built, which generates hidden states h_t at each time step t:

$$\vec{h}_t = LSTM(x_t, \overrightarrow{h_{t-1}}), \quad \overleftarrow{h}_t = LSTM\left(x_t, \overleftrightarrow{h_{t+1}}\right) \tag{1}$$

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \tag{2}$$

These concealed states are embedded in BERT, where every token embedding ei is treated as:

$$z_i = \mathrm{BERT}(h_i) \tag{3}$$

To perform sentiment classification, the final representation z may be passed to a softmax layer.

$$\hat{y} = softmax(Wz + b) \tag{4}$$

The learned parameters are W and b. It also increases the accuracy of the inclusion of these aspects; the mixture of local syntactic features and global semantic relations also increases the accuracy of sentiment predictions.

3.3 Evaluating metrics for analyzing sentiment analysis performance

To evaluate the performance of the sentiment analysis model, one applies a number of different quantitative metrics. The metrics being evaluated are, foremost, accuracy, precision, recall, and the F1 score, all of which derive from a confusion matrix constructed with predicted and actual sentiment class results.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Precision:

$$Precision \ \frac{TP}{TP + FP} \tag{6}$$

Recall:

$$Recall \ \frac{TP}{TP + FN} \tag{7}$$

F1 Score (harmonic mean of precision and recall):

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{8}$$

Also, ROC-AUC (Receiver Operating Characteristic - Area Under Curve) is used for examining the model's classification ability in the context of multi-class situations. Together, these metrics evaluate performance from different perspectives by considering the trade-off between the accuracy of the classification and the model's ability to generalize.

3.4 Security Measures in Data Collection and Processing

To ensure the privacy and security of sensitive user-generated information, including social media posts, reviews, and comments, our sentiment analysis framework will use various important security measures. To begin with, all the data that is obtained via the other external sources, such as Twitter and Reddit, is encrypted and, therefore, it is considered secure both when transmitting and storing it. Also, user identities are anonymized to safeguard them by keeping out personally identifiable information (PII) in the analysis process. In order to further protect data security, we embrace role-based access control (RBAC), where only data related to authorized personnel is allowed to access data. Finally, this framework is based on federated learning, which enables sentiment analysis to be conducted on user devices, therefore, saving sensitive information on the central servers and avoiding the exposure of sensitive information. All these security measures help to guarantee the integrity and privacy of user data and facilitate efficient sentiment analysis to curate the content.

3.5 Threat Models in AI Sentiment Analysis

Sentiment analysis AI models face a number of possible risks that can take away their accuracy, integrity, and use in an ethical way. The adversarial attacks are one of the most important risks, as attackers can use input information, social media posts, or reviews, with the help of tiny transformations that cannot be detected by humans but can be detected by the model, resulting in incorrect sentiment prediction. Another serious risk is the model inversion attacks, where the adversaries may use the output of the model to cause an inference concerning the sensitive information about the training data and disclose confidential information or the data of the user. Also, there is the case of data poisoning, where malicious data is introduced into the training process, and this compromises the performance of the model and may create bias in sentiment classification, which affects the reliability of the model. Moreover, sentiment manipulation is an unethical use of sentiment data to sway popular opinion or emotions, e.g., fake news or controlling the crowd in a crucial event like an election. In order to address these risks, it is necessary to introduce effective defense mechanisms, such as adversarial training, data verification processes, and the creation of ethical principles to maintain the integrity of the sentiment analysis systems and prevent irresponsible utilization of sentiment data.

IV. RESULTS

4.1 Examining Results from Sentiment Analysis

The newly developed BiLSTM-BERT model was put through testing with a balanced test dataset. Emphasis was put on three categories of sentiment: positive, negative, and neutral. As explained previously, the primary evaluation with baseline metrics included accuracy, precision, recall, and F1-score. To enrich our analysis, we implemented the macro and micro averaging methods, which are particularly useful in multi-class sentiment classification problems. As every class is given the same weight, averaging the values results in:

$$Macro - F1 = \frac{1}{N}\sum_{i=1}^{N} F1_i \qquad (9)$$

Where N is the total number of sentiment classes, and $F1_i$ represents the F1 score corresponding to class i.

Micro-averaging, unlike others, concentrates on the summation of instances and calculates the overall metrics as follows:

$$Micro - Precision = \frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N}(TP_i + FP_i)} \qquad (10)$$

$$Micro - Recall = \frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N}(TP_i + FN_i)} \qquad (11)$$

These metrics provide a complete understanding of performance. Our model achieved:

Macro-F1: 0.89

Micro-Precision: 0.91

Micro-Recall: 0.92

Such stability across all metrics is indicative of the model being generalizable and reliable.

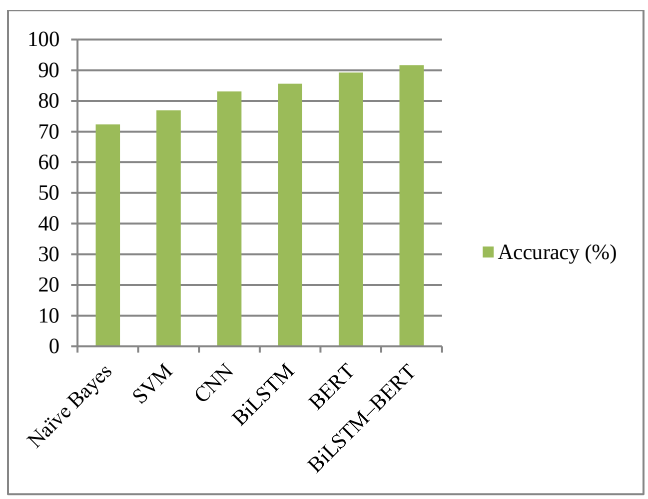

Fig. 3 Model Accuracy Comparison

Fig. 3 presents a bar chart measuring the accuracy of six models for sentiment classification. It can be noted that traditional models such as Naïve Bayes and SVM performed poorly, with accuracies of 72.4% and 76.9%, respectively, primarily due to their primitive feature extraction techniques. The accuracy of the deep learning models, CNN and BiLSTM, improved to 83.1% and 85.6% with the implementation of sophisticated algorithms that capture complex linguistic patterns. Moreover, the use of contextual embeddings in BERT further enhanced accuracy to 89.3%. The BiLSTM–BERT hybrid model proposed in this study surpassed the accuracy of all other methods, with an achieved accuracy of 91.6%. This finding exemplifies how the combination of temporal and contextual features results in better sentiment classification using deep learning models.

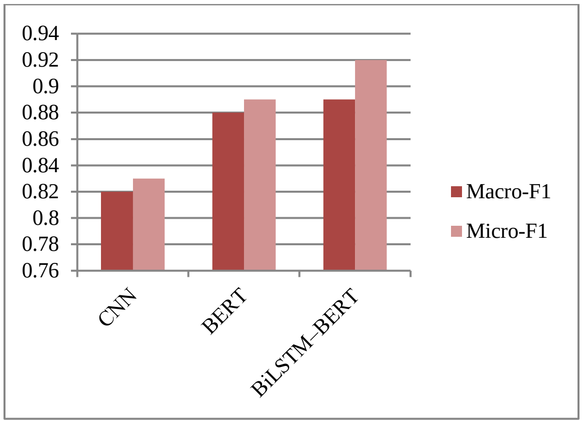

Fig. 4 Macro and Micro F1-Score Comparison

Fig. 4 demonstrates a grouped bar chart comparing the macro and micro F1 scores of CNN, BERT, and BiLSTM–BERT models on the F1-score. The former summarizes the model performance across all classes, while the latter focuses on the overall performance considering all instances. Once again, BiLSTM–BERT dominates both metrics with its macro and micro F1 scores of 0.89 and 0.92, respectively, showcasing sentiment performance consistency and classifier balance. BERT delivered decent results, too, achieving 0.88 and 0.89 for the macro and micro F1 scores, respectively. It was CNN who fell behind, most notably in macro-F1, suggesting that class imbalance or less frequent sentiments severely limited performance.

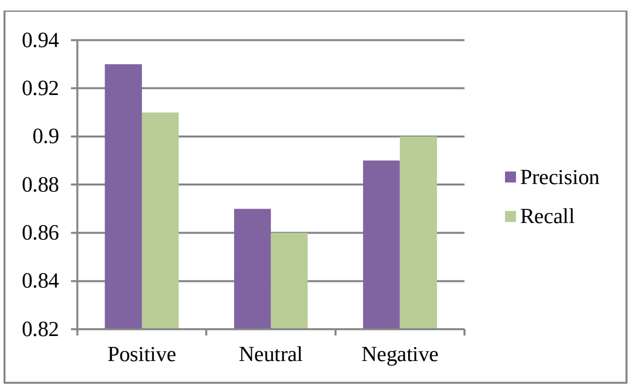

Fig. 5 Class-Wise Precision and Recall (BiLSTM–BERT Model)

Fig. 5 displays the results analyzed in terms of the precision and recall for the three sentiment classes: positive, neutral, and negative for the BiLSTM–BERT model. Precision and recall for the positive sentiment detection were 0.93 and 0.91, respectively, which are both high and demonstrate that positive sentiments are accurately captured. Negative sentiments also showed balanced values, with precision at 0.89 and recall at 0.90. Neutral often scores the lowest on precision and recall due to its ambiguity and recency-dependent nature, but managed to score 0.87 and 0.86, respectively. Overall, the analysis shows that the model performed well across different categories, with a slight drop in performance in more ambiguous cases.

4.2 Different AI Models Comparison

The comparative study was done using multiple algorithms. The confusion matrix was very helpful in calculating n-gram errors and understanding the damage. We calculated precision and recall for each class as well as overall per-class, macro, micro, and F1 scores. For a given class, let the confusion matrix be:

$$\begin{bmatrix} TP & FN \\ FP & TN \end{bmatrix} \quad (12)$$

As a result, the false positive rate (FPR) is derived as follows:

$$FPR = \frac{FP}{FP + TN} \quad (13)$$

The FPR for neutral sentiments, which are often misclassified, was the lowest for BiLSTM–BERT compared to the other models. In comparison, Naive Bayes exhibited an FPR of 0.21, CNN: 0.13, BERT: 0.08, and BiLSTM–BERT: 0.05. These findings suggest that the hybrid model would be effective in environments containing sensitive or high-stakes content due to the reduced error rate.

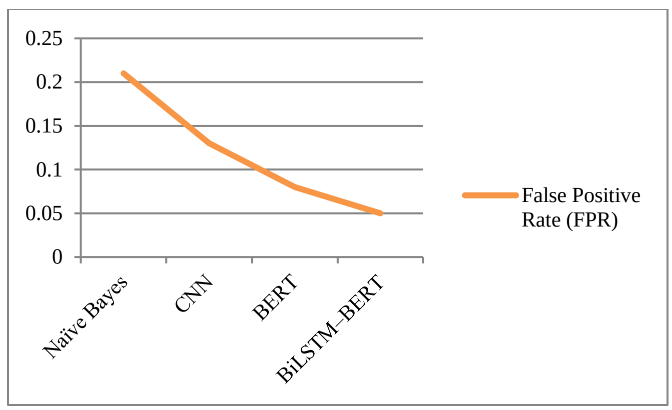

Fig. 6 False Positive Rate (FPR) per Model

Fig. 6 is a line graph displaying the FPRs of four chosen models: Naïve Bayes, CNN, BERT, and BiLSTM–BERT. BiLstm-BERT is the most reliable since it had the lowest FPR at 0.05 by showing the best control over false positives, thus proving its ability to filter and recommend content sensitive to sentiment. A lower FPR helps in getting fewer incorrectly predicted positives and makes a model better in terms of accuracy, while a high FPR is often bad and drops the correctness score. Naïve Bayes, which had the highest FPR with 0.21, posits them as not neutral or negative, misleadingly. This was improved for the CNN model, which reduced the FPR to 0.13, and then further improved by BERT to 0.08.

4.3 Discussion of Outcomes for Content Curation Approaches

As mentioned earlier, content recommendation systems take advantage of specific user interfaces that provide user enrichment with complex processed information using powerful computing resources, and a high-level automation stream for the Command-and-Control structure enabled by the computer gives every user a ready content stream customized to their tastes, which is streamed into the player. The computer also watches how the user behaves and optimally retunes the content flow to improve the user's experience. Tagging portions of the text as motivational or promotional in real-time increases the likely visibility, known as discoverability scoring, and ranking of the texts within user feeds, algorithmically promoted to them. Tags tracking particular user sentiments enable proper classification of the portion of text tagged, and, within user-defined pipelines, proper tagging algorithms mark sentient segments of text. Flagging also enables partial disablement of the rule that marks a user-defined sub-threshold. In a deep network-based decision-making hierarchy, the hard set $P(y = i) \geq 0.7$ for the softmax output can be adjusted post-environment altering without retraining the model adaptation to responsive states. Successful hedge-sensitive strategies are needed where the sentiment of content is more misleading and well-defined, and sharp identities are most prominent. Set-sustaining overarching permits greater reliance boundaries, which sets deep learning networks seem essential due to the highly inaccurate, volatile environment of the borders, where omitted signals significantly boost flexibility. Adding truth clauses in deep networks that allow policy changing of thresholds without retraining increases robustness and creates pathways for efficient, automated streams of choice that do not offer redundancy. The perfecting loop component of snippet selection has produced expunged filters on exposed interfaces, and thus is transparent to hidden constraints.

V. Discussion

The study's conclusion is that advanced AI systems are the most efficient application for sentiment analysis via strategic curation of content. The new BiLSTM-BERT hybrid structure examined in the paper outperformed all classical machine learning models and separate deep learning models. The performance can be attributed to the improved ability of the model to capture language sentiment with temporal learning through the BiLSTM and deep contextual embeddings of BERT. The precision and high macro and micro F1 score of the sentiment prediction is a good sign that the model has a promise of high protection against all types of sentiment and a high level of robustness, which is a superb text sentinel when using various data points. In particular, the application that is most feasible is the one with the lowest false positives for neutral sentiment. These outcomes point to the effectiveness of employing transformer-based culture wherever and whenever fine-tuned or with sequential models on intricate natural language processing issues. On the other hand, the revolutionary findings are the most important in terms of content curation. The sentiment analysis and classification feature allows one to adapt to emotional user requirements or community constraints in real-time. The responsiveness enhances the experience of the users as it produces healthier online environments.

There are also the disadvantages of this work, the most obvious being that sociolinguistics and data are a narrow discipline, although they represent a decent percentage of the internet and such sources. Auditory/visual performance and demographic factors (for example, age and ethnicity) will code-switch, and hyperbole can be overwhelming in influencing the model. In the same context, humor or sarcasm can make language turn non-standard. Not to forget, social platforms also come with their unique lingo, which varies per generation. Even though the accuracy and generalization of the BiLSTM–BERT model were deemed satisfactory, achieving set benchmarks required using an extensive amount of computational resources both during training and inference. Furthermore, the immediate redundancy model is said to offer in low-income areas for real-time tasks, which stands counterintuitive. Also, the abstractions made for model performance are heavily dependent on hyperparameter values, which are set, as well as the quality of pre-trained embeddings used to fine-tune the model. These settings could potentially lead to dramatic performance issues on previously unattested data with little to no return. In addition to the limitations mentioned, this model does not have the ability to comprehend multi-modal contexts. Especially considering multi-form text, picture, and even video sentiment is often used to convey messages. The emphasis only on text sentiment gives way to emotion-driven content detection, which can be most critical for tracking.

In addition to content curation, the AI-based sentiment analysis apparatus articulated in this chapter also has a substantial capacity to support the operations of enhanced levels of security. Through the sentiment analysis component, this apparatus will have the capacity to ascertain emotional cues and behavioral trends that it can use to trigger alarms for security-based risks, such as online harassment, simulated radicalization, or disinformation. For example, it is entirely possible that a piece of potentially harmful content (or a piece of content that displays rapid and drastic emotional shifts) being monitored might trigger a faster incident response from security personnel being tasked with assessing for potential risk. The security measures may be tailored to track and filter sensitive information on social media, and at the same time, data privacy legislation (e.g., GDPR, CCPA) is being observed, which will guarantee that no potentially harmful or confusing data is being floated.

Despite a strong possibility of content curation and influence with the help of sentiment analysis methods, certain ethical issues are also quite grave. Its best threat is the possibility of misusing the sentiment information in a way that one controls the readers by creating fabricated stories, manipulative messages, and propaganda campaigns, all of which can lead to brain manipulation. More than that, however, the AI sentiment analysis methods are also vulnerable to adversarial attacks that may undermine the sentiment analysis, and as a result prescribe unsuitable content or use emotional innuendo on clients and their responses. Thus, in order to support powerful offensive strategies and ethical use of sentiment analysis algorithms, there is a high demand. The work ought to be done going forward on how to create more robust AI systems that cannot be influenced adversarially, and apply the sentiment analysis tools in an ethical way so as to be accountable to the well-being of the user interaction and decision-making.

Although the sentiment analysis model introduced here can be used to curate content better, the potential of this field is endless, and more studies can be conducted in a direction that will cover even more serious problems. Among the potentially interesting opportunities is the application of sentiment analysis to identify fake reviews or spam comments on websites to make user-generated information more reliable and valid. More importantly, studies must focus on the directions of creating machine learning models without adversarial machine learning attacks in order to exclude the possibility of altering sentiment data with the purpose of malicious application in such fields as content recommendation or the control of opinions in the population. Future studies into creating superior performance sentiment analysis models must put in place a means of providing security measures, or a level of protection against malicious intent against the system, such as data poisoning, adversarial attacks, and other features that may wear down the integrity of the content curation infrastructure.

Automated modeling prevails in the usage of multilingual datasets and domain datasets in various areas and contexts, which enables the tools of analysis to offer a more definite audience and a reflection of content. It is also proposed that future studies should use these directions to develop on them and overcome limitations. Although the proposed models are strong and provide the correct data, the working models can also be incorporated into the mobile and edge computation machines to do real-time monitoring, which will also scale sentiment analytics.

Furthermore, proposed models can continue to analyze sentiments with specific Visual aids and audio signals (high definition), with emojis, images, and voice notes, which can bolster the accuracy of classifications, especially on social media platforms. By supporting AI engineers with content crafters, output accuracy increases user satisfaction, and automation for content delivery and moderation increases user satisfaction, while also focusing models into practical workflows, allowing for intelligent sentiment engines.

VI. Conclusion

This research demonstrates the effectiveness of AI-enabled sentiment analysis for strategic context curation. This paper examines the different models by creating a hybrid BiLSTM-BERT model. It demonstrates that a combination of temporal sequence-processing activity and contextual language representation results in better performance in sentiment classification. The model submitted gave a high accuracy, the highest recall, and good performance with a low false positive rate in view of different types of sentiment. The study confirms that the model has the capabilities of fully multilayered sentiment filtering and proposes/ranks contextual information according to the computed tone of emotion. The customized sentiment-sensitive curation system can also have many implications on the digital content strategies, which include more brand interactions and content publication policy fulfillment. However, AI systems have become dynamic and adaptive to handle all types of user-generated content that floods various online platforms. Potential applications of deep learning, along with natural language processing, include the provision of broad content intelligence, and the areas of multilingual/ multimodal and real-time systems are also likely to receive interest. Data security and data privacy are two important elements that should be integrated into AI-based sentiment analysis systems to ensure trust in the system and control the integrity of the digital content systems. Besides the fact that the proposed model generates better interaction between the user and customized content management, the model also incorporates secure data practices in a manner that does not affect sensitive user information. The further development of these safe data practices can also be discussed by future research with references to the new privacy rules, to be relevant to the new privacy legislation, and enhance the possibility of AI systems to identify and isolate security threats even in real time. In the production of artificial intelligence, sentiment analysis is also a significant element to establish an emotionally intelligent and user-friendly digital content ecosystem in marketing, education, social media policy, healthcare, etc.

References

[1] Akshayaa Raaja Shri, I. T., Kamalee, S., Rahul, B., & Menaka, S. R. (2022). Fine Motor Therapy Using Avatar-based AI for Autistic Children (Virtual Reality). *International Academic Journal of Science and Engineering*, *9*(2), 11–17. https://doi.org/10.9756/IAJSE/V9I2/IAJSE0908

[2] Alhumoud, S. O., & Al Wazrah, A. A. (2022). Arabic sentiment analysis using recurrent neural networks: a review. *Artificial Intelligence Review*, *55*(1), 707-748.

[3] Araque, O., Corcuera-Platas, I., Sánchez-Rada, J. F., & Iglesias, C. A. (2017). Enhancing deep learning sentiment analysis with ensemble techniques in social applications. *Expert Systems with Applications*, *77*, 236-246. https://doi.org/10.1016/j.eswa.2017.02.002

[4] Bosco, K. J., Pavalam, S. M., & Mpamije, L. J. (2023). Fundamental flip-flop design: comparative analysis. *Journal of VLSI circuits and systems*, *5*(01), 1-7. https://doi.org/10.31838/jvcs/05.01.01

[5] Cambria, E., Schuller, B., Xia, Y., & Havasi, C. (2017). New avenues in opinion mining and sentiment analysis. *IEEE Intelligent Systems*, 28(2), 15–21.

[6] Devi, R., & Priya, L. (2024). The Mechanism of Drug–Drug Interactions: A Systematic Review. *Clinical Journal for Medicine, Health and Pharmacy*, *2*(3), 32-41.

[7] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, June). Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 conference of the North*

American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers) (pp. 4171-4186). https://doi.org/10.18653/v1/N19-1423

[8] Dorofte, M., & Krein, K. (2024). Novel approaches in AI processing systems for their better reliability and function. *International Journal of Communication and Computer Technologies*, *12*(2), 21-30.

[9] Etuk, H. S., Ebong, G. A., Ekot, A. E., Ekpo, B. O., & Ayi, A. A. (2024). Mineral and elemental compositions of suspended particulate matter (SPM) and sediments from major rivers in the Southeastern Nigeria. *International Journal of Aquatic Research and Environmental Studies*, *4*(1), 71-89. http://doi.org/10.70102/IJARES/V4I1/7

[10] Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM*, *56*(4), 82-89. https://doi.org/10.1145/2436256.2436274

[11] Gajula, Y. (2025). Sentiment-Aware Recommendation Systems in E-Commerce: A Review from a Natural Language Processing Perspective. https://doi.org/10.48550/arXiv.2505.03828

[12] Ghiassi, M., Skinner, J., & Zimbra, D. (2013). Twitter brand sentiment analysis: A hybrid system using n-gram analysis and dynamic artificial neural network. *Expert Systems with applications*, *40*(16), 6266-6282. https://doi.org/10.1016/j.eswa.2013.05.057

[13] Gowindasamy, M. (2018). Impact of emotional intelligence on the subjective well-being of Indian female entrepreneurs in Klang valley. *International Academic Journal of Organizational Behavior and Human Resource Management*, *5*(1), 26-35. https://doi.org/10.9756/IAJOBHRM/V5I1/1810002

[14] Hakimov, N., Karimov, N., Reshetnikov, I., Yusufjonova, N., Aldasheva, S., Soatova, N., ... & Bozorova, D. (2024). Mechanical Marvels: Innovations in Engineering During the Islamic Golden Age. *Archives for Technical Sciences*, *31*(2), 159-67. https://doi.org/10.70102/afts.2024.1631.159

[15] Harris, S., Hadi, H. J., Ahmad, N., & Alshara, M. A. (2024). Fake news detection revisited: An extensive review of theoretical frameworks, dataset assessments, model constraints, and forward-looking research agendas. *Technologies*, *12*(11), 222. https://doi.org/10.3390/technologies12110222

[16] Huang, J. (2024). Impact of Non-performing Corporate Assets on Shareholder's Equity and Return on the Application of AI and Blockchain Technologies. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 15*(3), 412-423. https://doi.org/10.58346/JOWUA.2024.I3.027

[17] Latif, A. Z., & Agrab, A. S. (2022). Study of Global Financial Crises and their Effects on Accounting Systems. *International Academic Journal of Social Sciences*, *9*(2), 21–26. https://doi.org/10.9756/IAJSS/V9I2/IAJSS0910

[18] Li, N., & Huang, F. (2024). Evaluating the Financial Returns on Investment in Sustainable Enterprise Digitalization Initiatives Using AI Information System. *Journal of Internet Services and Information Security, 14*(4), 21-44. https://doi.org/10.58346/JISIS.2024.I4.002

[19] Liu, B. (2020). *Sentiment analysis: Mining opinions, sentiments, and emotions* (2nd ed.). Cambridge University Press.

[20] Liu, B. (2022). *Sentiment analysis and opinion mining*. Springer Nature. https://doi.org/10.1007/978-3-031-02145-9

[21] Luo, B., Lau, R. Y., Li, C., & Si, Y. W. (2022). A critical review of state-of-the-art chatbot designs and applications. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *12*(1), e1434. https://doi.org/10.1002/widm.1434

[22] Mahdavipur, M., & Ghermezi, S. (2018). Investigating Role and Position of Technical Training in Human Resource Development in Chaharmahal and Bakhtiari Province, Iran (Case Study: Trained Employees of Private Sector). *International Academic Journal of Economics*, *5*(1), 47–62. https://doi.org/10.9756/IAJE/V5I1/1810006

[23] Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams engineering journal*, *5*(4), 1093-1113. https://doi.org/10.1016/j.asej.2014.04.011

[24] Moretti, A., & Tanaka, H. (2025). Securing Multi-Modal Medical Data Management System using Blockchain and the Internet of Medical Things. *Global Journal of Medical Terminology Research and Informatics*, *3*(1), 15-21.

[25] Nallasivamani, P., Nishanth, R., Rameshkrishnan, M., Soundar, M., & Mounika, S. (2023). Clothing Recommender System using Deep Learning. *International Journal of Advances in Engineering and Emerging Technology*, *14*(1), 58-63.

[26] Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends® in Information Retrieval*, 2(1–2), 1–135. https://doi.org/10.1561/1500000011

[27] Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment classification using machine learning techniques. https://doi.org/10.48550/arXiv.cs/0205070

[28] Poria, S., Cambria, E., Bajpai, R., & Hussain, A. (2017). A review of affective computing: From unimodal analysis to multimodal fusion. *Information fusion*, *37*, 98-125. https://doi.org/10.1016/j.inffus.2017.02.003

[29] Rahman, M. A., & Rahman, A. (2025). A Systematic Review of Intelligent Support Systems for Strategic Decision-Making Using Human-Ai Interaction in Enterprise Platforms. *Available at SSRN 5269458*.

[30] Rao, A., & Menon, P. (2024). A Review of Membrane Filtrating Methods for Contaminant/Pollution Removal in Water and Sewage Treatment. *Engineering Perspectives in Filtration and Separation*, 1-6.

[31] Rojas, C., & García, F. (2024). Optimizing traffic flow in smart cities: A simulation-based approach using IoT and AI integration. *Association Journal of Interdisciplinary Technics in Engineering Mechanics*, *2*(1), 19-22.

[32] Saxena, R. R. (2024). Examining Reactions about COVID-19 Vaccines: A Systematic Review of Studies Utilizing Deep Learning for Sentiment Analysis. *Authorea Preprints*.

[33] Socher, R., Perelygin, A., Wu, J., Chuang, J., Manning, C. D., Ng, A. Y., & Potts, C. (2013, October). Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing* (pp. 1631-1642).

[34] Thelwall, M. (2016). The Heart and soul of the web? Sentiment strength detection in the social web with SentiStrength. In *Cyberemotions: Collective emotions in cyberspace* (pp. 119-134). Cham: Springer International Publishing.