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Sentiments Analysis and Emotion Detection Through Deep Learning: A Systematic Review

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ABSTRACT:
Sentiment Analysis and Emotion Detection are important tasks in the field of Natural Language Processing, aiming to identify subjective information such as opinions, attitudes, and emotions from textual data. With the exponential growth of social media platforms, online reviews, and digital communication, the need for automated techniques to analyze sentiments has significantly increased. This study explores various Machine Learning (ML) and Deep Learning (DL) models used for sentiment classification and emotion recognition. Traditional ML approaches such as Support Vector Machines (SVM), Naïve Bayes, and Logistic Regression rely heavily on feature extraction techniques like TF-IDF and Bag-of-Words. While these models provide satisfactory performance, they often fail to capture contextual and semantic relationships within text. To overcome these limitations, DL models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Transformer-based architectures have been widely adopted. This study presents a comparative analysis of ML and DL techniques based on accuracy, precision, recall, and F1-score. It also discusses the role of pre-trained language models like BERT in improving performance. Experimental results indicate that DL models, especially transformer-based approaches, outperform traditional ML models in capturing complex emotional nuances. The study highlights challenges such as data imbalance, sarcasm detection, and multilingual sentiment analysis, and suggests future directions for improving emotion detection systems.
Keywords: Sentiment Analysis, Emotion Detection, Machine Learning, Deep Learning

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I INTRODUCTION

In the era of digital communication, the rapid growth of online platforms has generated an enormous amount of textual data, making it essential to develop intelligent systems capable of analyzing human opinions and emotions. Sentiment Analysis and Emotion Detection have emerged as significant research areas within Natural Language Processing, focusing on extracting subjective information from text such as attitudes, feelings, and opinions. These techniques are widely used in applications including social media monitoring, customer feedback analysis, product review evaluation, and decision-making systems [1, 2].

Sentiment Analysis primarily aims to classify textual data into predefined categories such as positive, negative, or neutral. In contrast, Emotion Detection goes beyond polarity classification and identifies specific emotional states such as happiness, anger, sadness, fear, and surprise. With the widespread use of platforms like Twitter, Facebook, and Instagram, users generate vast amounts of unstructured and dynamic text data daily. This has created a strong demand for automated tools that can efficiently analyze and interpret such data in real time [3].

Traditional approaches to sentiment analysis relied heavily on lexicon-based techniques and classical Machine Learning algorithms. Methods such as Support Vector Machines (SVM), Naïve Bayes, and Decision Trees have been widely used due to their simplicity and effectiveness. These models typically depend on manual feature extraction techniques such as Bag-of-Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF). Although these approaches perform well on structured datasets, they often fail to capture contextual meaning, sarcasm, and complex linguistic patterns present in real-world text [4, 5].

The emergence of Deep Learning has significantly transformed the field of sentiment analysis and emotion detection. Deep Learning models are capable of automatically learning hierarchical feature representations from raw text data, reducing the need for manual feature engineering. Models such as Convolutional Neural

Networks (CNNs) are effective in capturing local patterns in text, while Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are designed to handle sequential data and capture long-term dependencies. These models have demonstrated superior performance compared to traditional Machine Learning techniques, especially in large-scale datasets [6].

More recently, transformer-based architectures have revolutionized Natural Language Processing tasks. Models such as BERT have introduced a context-aware understanding of language by considering both left and right contexts simultaneously. This bidirectional approach enables the model to better understand the semantic relationships between words, leading to improved accuracy in sentiment classification and emotion recognition tasks. Furthermore, pre-trained language models and transfer learning techniques have reduced the requirement for large labeled datasets, making advanced models more accessible [7, 8].

Despite these advancements, several challenges remain in the domain of sentiment analysis and emotion detection. One of the major issues is handling noisy and unstructured data, particularly from social media platforms where text often includes slang, abbreviations, emojis, and grammatical inconsistencies. Detecting sarcasm and irony remains a complex problem, as the intended meaning of a sentence may differ significantly from its literal interpretation. Additionally, multilingual sentiment analysis poses difficulties due to linguistic diversity and the lack of labeled datasets in many languages [9].

Another important challenge is class imbalance, where certain sentiment or emotion categories are underrepresented in datasets, leading to biased model performance. Real-time sentiment analysis also requires efficient and computationally optimized models that can process large volumes of data quickly without compromising accuracy. Addressing these challenges is crucial for developing robust and scalable sentiment analysis systems.

This study aims to provide a comprehensive overview of various Machine Learning and Deep Learning approaches used for sentiment analysis and emotion detection. It presents a comparative analysis of different models based on their performance, advantages, and limitations. The study also highlights recent advancements in transformer-based models and discusses future research directions, including hybrid approaches, multilingual models, and real-time implementation strategies. By exploring both traditional and modern techniques, this work contributes to a deeper understanding of how intelligent systems can effectively interpret human emotions from textual data.

II. LITERATURE REVIEW

R. Boukhenoun, K. Messaoudi, and E.-B. Bourennane (2025) presented a comprehensive study on real-time emotion detection by comparing traditional Machine Learning (ML) techniques with advanced Deep Learning (DL) models using a Streamlit-based Natural Language Processing (NLP) application. The authors focused on evaluating the performance of classical models such as Support Vector Machines (SVM), Naïve Bayes, and Logistic Regression against modern deep learning architectures including Recurrent Neural Networks (RNN) and transformer-based models. Their system was designed for real-time deployment, enabling user interaction through a web interface. Experimental results demonstrated that deep learning models significantly outperform traditional ML methods in terms of accuracy and contextual understanding, especially in handling complex linguistic patterns. However, the study also highlighted that ML models are computationally less expensive and easier to implement, making them suitable for lightweight applications. The research emphasized the trade-off between performance and computational cost, concluding that DL models are preferable for high-accuracy requirements, while ML models remain viable for resource-constrained environments.

M. G. Rao et al. (2025) proposed a multimodal deep learning framework for identifying and categorizing deceptive emotions by integrating multiple data sources such as facial expressions, speech signals, and textual information. The study leveraged Convolutional Neural Networks (CNNs) for image processing and Long Short-Term Memory (LSTM) networks for sequential data analysis, enabling the system to capture both spatial and temporal features. The fusion of multimodal data significantly improved the detection of deceptive emotions compared to unimodal approaches. The authors demonstrated that combining different modalities enhances robustness and accuracy, particularly in real-world scenarios where emotional cues may be subtle or ambiguous. Their findings indicated that multimodal deep learning systems can effectively detect inconsistencies across modalities, making them highly suitable for applications such as security, psychological analysis, and human-computer interaction.

J. S. Kallimani et al. (2025) developed an automated hybrid model combining Deep Neural Networks (DNN) and Support Vector Machines (SVM) for facial emotion classification. In this work, DNN was utilized for feature extraction due to its ability to learn hierarchical representations, while SVM was employed as a classifier to enhance decision boundaries. The hybrid approach aimed to leverage the strengths of both deep learning and traditional machine learning techniques. The results showed that the proposed DNN-SVM model achieved higher accuracy and better generalization compared to standalone models. The study highlighted that integrating deep feature extraction with efficient classifiers can significantly improve performance, especially when dealing with limited datasets. This approach also reduced overfitting issues commonly associated with deep learning models.

K. Anusha et al. (2025) introduced a deep learning-based emotion detection system that integrates both image and audio inputs to enhance prediction accuracy. The proposed system utilized CNNs for extracting visual features from facial images and audio processing techniques such as Mel-frequency cepstral coefficients (MFCCs) combined with deep neural networks for speech analysis. By combining these modalities, the system achieved improved performance in recognizing human emotions under diverse conditions. The study demonstrated that audio-visual fusion provides complementary information,

thereby increasing robustness against noise and environmental variations. The authors concluded that multimodal systems are more reliable than single-modality systems and have significant potential in applications such as virtual assistants and affective computing.

M. K. B et al. (2024) conducted a survey on emotion detection using facial recognition techniques, providing an overview of various methodologies, datasets, and challenges in the field. The paper discussed traditional approaches such as feature-based methods and modern deep learning techniques including CNNs and transfer learning models. It also highlighted key challenges such as variations in lighting, occlusion, and facial pose, which affect the performance of emotion detection systems. The survey emphasized the importance of large annotated datasets and advanced preprocessing techniques for improving model accuracy. Additionally, the authors discussed emerging trends such as real-time emotion recognition and multimodal integration, suggesting future research directions.

L. Huang (2024) presented a survey on deep learning approaches for text sentiment analysis, focusing on various neural network architectures such as CNNs, RNNs, and transformers. The study explored how deep learning models can capture contextual and semantic relationships in textual data more effectively than traditional methods. It highlighted the advantages of pretrained language models, such as improved accuracy and reduced training time. The survey also discussed challenges such as data imbalance, domain adaptation, and interpretability of models. The findings indicated that deep learning has become the dominant approach in sentiment analysis due to its superior performance and scalability.

Y. Wu et al. (2024) investigated the application of the BERT (Bidirectional Encoder Representations from Transformers) model in sentiment analysis. The study demonstrated how BERT's bidirectional context understanding significantly improves the accuracy of emotion and sentiment classification tasks. By fine-tuning pretrained BERT models, the authors achieved state-of-the-art results on multiple datasets. The research highlighted that transformer-based models outperform traditional and earlier deep learning approaches due to their ability to capture long-range dependencies and contextual nuances. The paper concluded that BERT and similar models are highly effective for complex NLP tasks.

T. S. Konappanavar et al. (2023) developed a real-time facial emotion detection system using machine learning techniques. The proposed system employed feature extraction methods such as Haar cascades for face detection and traditional classifiers like SVM and KNN for emotion classification. The study demonstrated that ML-based systems can achieve satisfactory performance with lower computational requirements, making them suitable for real-time applications. However, the authors noted that these methods may struggle with complex emotional expressions and varying environmental conditions compared to deep learning approaches.

J. Deng and F. Ren (2023) proposed a multi-label emotion detection framework that incorporates emotion-specific feature extraction and emotion correlation learning. The study addressed the limitation of single-label classification by enabling the detection of multiple emotions simultaneously. The proposed model utilized deep learning techniques to capture the relationships between different emotional states. Experimental results showed improved performance in multi-label classification tasks, highlighting the importance of considering emotional correlations in real-world scenarios where multiple emotions often coexist.

M. Bhanupriya et al. (2023) introduced EmotionTracker, a real-time facial emotion detection system using OpenCV and DeepFace. The system leveraged pre-trained deep learning models for face recognition and emotion classification, enabling efficient and accurate predictions. The use of OpenCV facilitated real-time video processing, while DeepFace provided robust feature extraction capabilities. The study demonstrated that combining computer vision libraries with deep learning frameworks can result in practical and scalable emotion detection systems. The authors concluded that such systems are highly applicable in areas such as surveillance, user behavior analysis, and interactive applications.

III. EMOTION DETECTION USING ML AND DL MODELS

Emotion Detection is an advanced task in Natural Language Processing that focuses on identifying human emotions such as happiness, anger, sadness, fear, and surprise from textual data. With the increasing availability of data from social media, chat systems, and reviews, automated emotion detection systems have become essential for applications like mental health analysis, customer feedback, and human-computer interaction.

Emotion detection can be implemented using both Machine Learning (ML) and Deep Learning (DL) models. The overall process involves several stages, including data collection, preprocessing, feature extraction, model training, and evaluation.

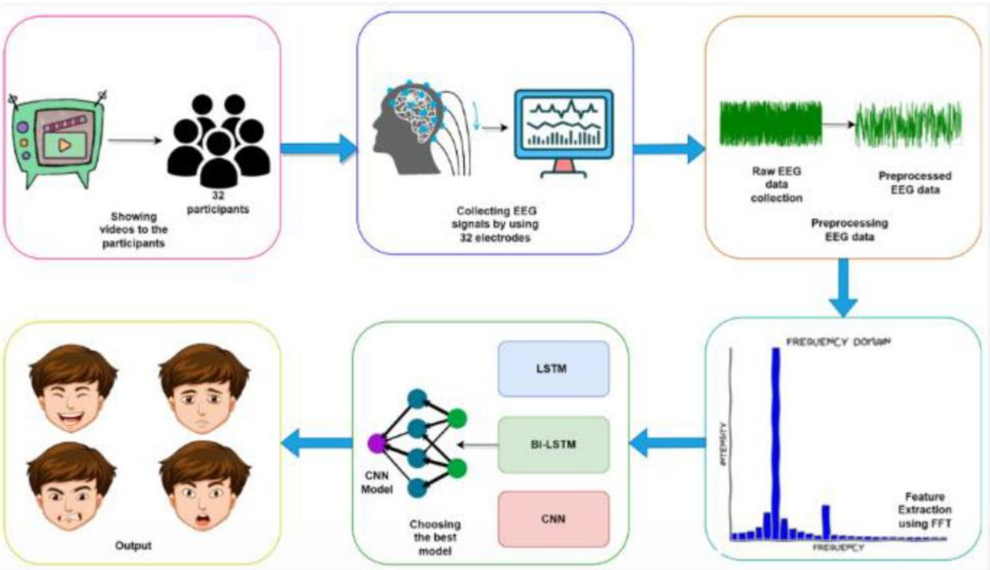

Figure 1: Complete workflow of the proposed emotion recognition pipeline from DEAP dataset.

3.1 Emotion Detection using Machine Learning (ML)

Machine Learning models are traditional approaches that rely on manual feature engineering. Common ML algorithms include:

- Support Vector Machine (SVM): Support Vector Machine (SVM) is a supervised Machine Learning algorithm widely used for classification tasks such as sentiment analysis and emotion detection in Natural Language Processing. The main objective of SVM is to find an optimal hyperplane that separates data points of different classes with maximum margin. In the context of text analysis, each document or sentence is converted into a numerical feature vector using techniques like TF-IDF or Bag-of-Words. SVM works by identifying support vectors, which are the critical data points closest to the decision boundary. These points help define the position of the hyperplane. For emotion detection, SVM can classify text into categories such as happy, sad, angry, etc., based on learned patterns in the training data.

Advantages:

- Effective in high-dimensional data (like text)
- Works well with small and medium datasets
- High accuracy in classification tasks

Limitations:

- Requires careful parameter tuning (kernel selection)
- Not efficient for very large datasets
- Does not capture sequential context in text

Naïve Bayes (NB): Naïve Bayes is a probabilistic classifier based on Bayes' Theorem, which assumes that features are independent of each other. Despite this “naïve” assumption, it performs very well in text classification tasks, including emotion detection. In this approach, the probability of a sentence belonging to a particular emotion class is calculated based on the frequency of words present in the text. For example, words like “happy,” “great,” or “excited” increase

• the probability of the "positive" or "joy" class. Naïve Bayes is commonly used with text features such as Bag-of-Words or TF-IDF. It is simple, fast, and efficient, making it suitable for real-time applications.

• Logistic Regression: Logistic Regression is a statistical classification algorithm used to predict the probability of a categorical outcome. In emotion detection, it is used to classify text into different emotional categories based on input features. Unlike linear regression, Logistic Regression uses a sigmoid function to map predicted values into probabilities between 0 and 1. The model learns weights for each feature (word) and predicts the class with the highest probability.

Advantages:
• Easy to implement and interpret
• Works well for binary and multi-class classification
• Less computationally expensive

Limitations:
• Limited ability to capture complex relationships
• Performance depends on feature quality
• Not suitable for highly non-linear data

Process in ML:
• Text is converted into numerical form using techniques like TF-IDF or Bag-of-Words
• Features are manually selected
• Classifier predicts emotion labels

Advantages:
• Simple and fast
• Works well on small datasets
• Low computational cost

Limitations:
• Cannot capture context effectively
• Poor performance on complex sentences (sarcasm, irony)

3.2 Emotion Detection using Deep Learning (DL)
Deep Learning models automatically learn features from raw text and capture contextual relationships.

Common DL Models:
• Convolutional Neural Networks (CNN)
• Recurrent Neural Networks (RNN)
• Long Short-Term Memory (LSTM)
• Transformer models like BERT

Process in DL:
• Text is converted into word embeddings (Word2Vec, GloVe)
• Neural networks learn patterns automatically
• Sequential models capture context and dependencies

Advantages:
• High accuracy
• Captures semantic meaning
• Handles large datasets effectively

Limitations:
• Requires more data
• High computational cost
• Longer training time

IV. METHODOLOGY

The methodology for Sentiment Analysis and Emotion Detection using Machine Learning (ML) and Deep Learning (DL) models involves a systematic pipeline that transforms raw textual data into meaningful emotional insights. This process is a core application of Natural Language Processing and includes multiple stages such as data collection, preprocessing, feature extraction, model training, and evaluation.

2. Data Collection
The first step involves collecting textual data from various sources such as social media platforms, online reviews, and publicly available datasets. Common sources include Twitter, Facebook, and product review datasets like IMDb. These datasets contain user-generated content expressing opinions and emotions, which are essential for training sentiment analysis models.

3. Data Preprocessing
Raw text data is often noisy and unstructured. Therefore, preprocessing is necessary to clean and normalize the data. The following steps are performed:
• **Tokenization:** Splitting text into words or tokens
• **Lowercasing:** Converting all text to lowercase
• **Stop-word Removal:** Removing common words (e.g., "is", "the")
• **Noise Removal:** Eliminating special characters, URLs, emojis

4. Feature Extraction
Text data must be converted into numerical form before feeding it into models.
For ML Models:

- Bag-of-Words (BoW)
- Term Frequency-Inverse Document Frequency (TF-IDF)

For DL Models:

- Word Embeddings (Word2Vec, GloVe)
- Contextual embeddings using BERT

Feature extraction plays a crucial role in determining the accuracy of the model.

5. Model Training

In this stage, different ML and DL models are trained on the processed dataset.

Machine Learning Models:

- Support Vector Machine (SVM)
- Naïve Bayes (NB)
- Logistic Regression

These models use extracted features to classify emotions.

Deep Learning Models:

- Convolutional Neural Networks (CNN)
- Recurrent Neural Networks (RNN)
- Long Short-Term Memory (LSTM)

DL models automatically learn features and capture contextual relationships in text.

6. Emotion Classification

After training, the model predicts the emotional category of input text. The output classes may include:

- Positive / Negative / Neutral (Sentiment Analysis)
- Happy, Sad, Angry, Fear, Surprise (Emotion Detection)

The classification results depend on the learned patterns from training data.

V. CONCLUSION

Sentiment Analysis and Emotion Detection have become essential components of modern intelligent systems, enabling the extraction of meaningful insights from vast amounts of textual data. As a key application of Natural Language Processing, these techniques play a crucial role in understanding human opinions, behaviors, and emotional patterns across domains such as social media, healthcare, business analytics, and customer relationship management.

This study has explored both traditional Machine Learning and advanced Deep Learning approaches for sentiment and emotion classification. Machine Learning models such as Support Vector Machines, Naïve Bayes, and Logistic Regression offer simplicity, faster training, and good performance on smaller datasets. However, their reliance on manual feature engineering limits their ability to capture contextual and semantic relationships in complex textual data. In contrast, Deep Learning models such as CNNs, RNNs, and LSTM networks provide automatic feature extraction and improved performance by effectively learning patterns from large datasets.

Furthermore, transformer-based models like BERT have significantly advanced the field by introducing context-aware language understanding. These models outperform traditional and earlier deep learning approaches by capturing bidirectional context and deeper semantic meaning, leading to higher accuracy in sentiment classification and emotion detection tasks.

Despite these advancements, several challenges persist, including handling sarcasm and irony, managing noisy and unstructured data, addressing class imbalance, and performing multilingual sentiment analysis. Additionally, the need for computational efficiency and real-time processing remains an important consideration for practical applications.

In conclusion, while Deep Learning and transformer-based models have demonstrated superior performance, the integration of Machine Learning and Deep Learning techniques through hybrid approaches holds great promise for future research. Further improvements in model efficiency, dataset diversity, and multilingual capabilities will enhance the robustness and applicability of sentiment analysis systems. This study highlights that continued innovation in this domain will be vital for developing intelligent systems capable of accurately interpreting human emotions and supporting data-driven decision-making.

REFERENCES

[1]. R. Boukhenoun, K. Messaoudi and E. -B. Bourennane, "Real-Time Emotion Detection: A Comparative Study of traditional ML and advanced DL Models in Streamlit Application for Natural Language Processing," *2025 7th International Conference on Pattern Analysis and Intelligent Systems (PAIS)*, Laghouat, Algeria, 2025, pp. 1-6.

[2]. M. G. Rao, B. Ashwini, Vasudeva, S. B. M. Ahamed, N. Chetty and H. Priyanka, "Multimodal Deep Learning for Identifying and Categorizing Deceptive Emotions," *2025 2nd International Conference on Software, Systems and Information Technology (SSITCON)*, Tumkur, India, 2025, pp. 1-7.

[3]. J. S. Kallimani, R. S. B, A. N and S. R, "An Automated Deep Neural Network (DNN) and

Support Vector Machine (SVM) Model for Facial Emotion Classification," *2025 2nd International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE)*, Chennai, India, 2025, pp. 1-7.

[4]. K.Anusha, K.Karthika, R.Praveen, S.Madhan, S. M. Kumar and G. Pragatheesh, "Image and Audio Based Emotion Detection using Deep Learning," *2025 3rd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, Coimbatore, India, 2025, pp. 1-6.

[5]. M. K. B *et al*., "A survey on emotion detection and analysis using facial recognition," *2024 International Conference on Augmented Reality, Intelligent Systems, and Industrial Automation (ARIIA)*, Manipal, India, 2024, pp. 1-5.

[6]. L. Huang, "Deep learning for text sentiment analysis: A survey," *Applied and Computational Engineering*, vol. 104, pp. 135–139, 2024.

[7]. Y. Wu, Z. Jin, C. Shi, P. Liang and T. Zhan, "Research on the application of deep learning-based BERT model in sentiment analysis," Applied and Computational Engineering, vol. 67, pp. 280–286, 2024.

[8]. T. S. Konappanavar, J. S. Loni, S. Adhyapak and S. B. Patil, "Real-Time Facial Emotion Detection Using Machine Learning," *2023 2nd International Conference on Futuristic Technologies (INCOFT)*, Belagavi, Karnataka, India, 2023, pp. 1-5.

[9]. J. Deng and F. Ren, "Multi-Label Emotion Detection via Emotion-Specified Feature Extraction and Emotion Correlation Learning," in *IEEE Transactions on Affective Computing*, vol. 14, no. 1, pp. 475-486, 1 Jan.-March 2023.

[10]. M. Bhanupriya, N. Kirubakaran and P. Jegadeeshwari, "EmotionTracker: Real-time Facial Emotion Detection with OpenCV and DeepFace," *2023 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI)*, Chennai, India, 2023, pp. 1-4.

[11]. W. Wu, M. Wu and K. Yu, "Climate and Weather: Inspecting Depression Detection via Emotion Recognition," *ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Singapore, Singapore, 2022, pp. 6262-6266.

[12]. D. E. Cahyani, A. P. Wibawa, D. D. Prasetya, L. Gumilar, F. Akhbar and E. R. Triyulinar, "Emotion Detection in Text Using Convolutional Neural Network," *2022 International Conference on Electrical and Information Technology (IEIT)*, Malang, Indonesia, 2022, pp. 372-376.

[13]. S. K. Sooch and D. Anand, "Emotion Classification and Facial Key point detection using AI," *2021 2nd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS)*, Ernakulam, India, 2021, pp. 1-5.

[14]. H. S. Hemanth Kumar, Y. P. Gowramma, S. H. Manjula, D. Anil and N. Smitha, "Comparison of various ML and DL Models for Emotion Recognition using Twitter," *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, Tirunelveli, India, 2021, pp. 1332-1337.

[15]. W. Etaiwi, D. Suleiman and A. Awajan, "Deep learning based techniques for sentiment analysis: A survey," *Informatica*, vol. 45, no. 7, 2021.

[16]. Y. Chen and Z. Zhang, "Research on text sentiment analysis based on CNNs and SVM," in *Proc. 13th IEEE Conf. Industrial Electronics and Applications (ICIEA)*, 2018.

[17]. A. Hassan and A. Mahmood, "Convolutional recurrent deep learning model for sentence classification," *IEEE Access*, vol. 6, pp. 13949–13957, 2018.

[18]. M. Y. Day and Y. D. Lin, "Deep learning for sentiment analysis on Google Play consumer reviews," in *Proc. IEEE Int. Conf. Information Reuse and Integration (IRI)*, 2017.

[19]. F. Luo, C. Li and Z. Cao, "Affective-feature-based sentiment analysis using SVM classifier," in *Proc. IEEE Int. Conf. Computer Supported Cooperative Work in Design*, 2016.

[20]. V. Yeole, P. V. Chavan and M. C. Nikose, "Opinion mining for emotions determination," in *Proc. IEEE Int. Conf. Innovative Information, Embedded and Communication Systems*, 2015.