



A Hybrid Artificial Intelligence Framework for Emotion-Aware Domestic Violence Detection Using Video Analytics

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Abstract— The increasing use of digital communication platforms has created opportunities for identifying emotional behavior and detecting potentially harmful activities through intelligent data analysis. This paper presents an artificial intelligence-based framework for emotion recognition from social media text with an extension for identifying violent activities from surveillance videos and facial expressions captured through a live webcam. The proposed system utilizes a Twitter-based emotion dataset containing positive, neutral, and negative sentiments. Initially, the textual data undergoes preprocessing, including noise removal, stop-word elimination, tokenization, and feature extraction using the Term Frequency–Inverse Document Frequency (TF–IDF) technique. The processed data are divided into training and testing sets using an 80:20 ratio. Multiple machine learning and deep learning models, including Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM), are trained and evaluated to analyze their emotion classification performance. Experimental results indicate that ensemble and deep learning approaches achieve superior classification accuracy while maintaining reliable prediction capability across different emotional categories. The developed framework further extends its functionality by examining CCTV video streams to recognize violent activities and by employing a webcam-based facial emotion recognition module for real-time monitoring. By integrating text analytics, computer vision, and deep learning techniques into a unified framework, the proposed system demonstrates an effective approach for supporting early identification of emotional distress and suspicious activities, offering potential applications in public safety, digital surveillance, and intelligent monitoring systems.

Keywords— Emotion recognition, social media analysis, sentiment classification, violence detection, machine learning, deep learning, Support Vector Machine (SVM), Random Forest, Decision Tree, Naïve Bayes, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Term Frequency–Inverse Document Frequency (TF–IDF), CCTV video analysis, facial emotion recognition, webcam-based monitoring, text

preprocessing, intelligent surveillance, public safety, artificial intelligence.

1. INTRODUCTION

The rapid growth of social networking platforms and digital communication technologies has transformed the way individuals express their emotions, opinions, and experiences. Every day, millions of users share text messages, comments, images, and videos through online platforms, creating a large volume of data that reflects public emotions and behavioral patterns [4]. While these platforms promote communication and information sharing, they also provide opportunities for abusive behavior, online harassment, hate speech, and activities that may lead to physical violence. Identifying such harmful behavior at an early stage has become an important research challenge in the fields of artificial intelligence, natural language processing, and computer vision. Traditional manual monitoring approaches are often inefficient due to the continuously increasing amount of digital content, making automated analysis essential for real-time monitoring and timely intervention. Machine learning and deep learning techniques have therefore emerged as effective solutions for recognizing emotions and identifying suspicious activities from both textual and visual data [12].

Recent developments in intelligent data analysis have significantly improved the ability of computational models to understand human emotions and behavioral patterns from multiple data sources. In text-based emotion analysis, preprocessing techniques such as stop-word removal, tokenization, and feature extraction using Term Frequency–Inverse Document Frequency (TF–IDF) convert unstructured social media content into numerical representations suitable for machine learning models [8]. Classification algorithms including Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) have demonstrated promising performance in recognizing emotional states from textual information. Similarly, advances in computer vision have enabled intelligent systems to analyze surveillance videos and facial expressions for identifying violent activities and emotional reactions. The integration of text analytics with



image and video processing provides a comprehensive framework for monitoring potentially harmful situations using multiple sources of information [17].

This paper presents an intelligent emotion recognition and violence detection framework that combines social media text classification with computer vision techniques for real-time monitoring. The proposed methodology initially preprocesses a Twitter-based emotion dataset through text cleaning, TF-IDF feature extraction, normalization, and an 80:20 training and testing data split before training multiple machine learning and deep learning models [10]. The performance of Naïve Bayes, Decision Tree, Random Forest, SVM, CNN, and LSTM is evaluated through comparative analysis to determine their effectiveness in emotion classification. Furthermore, the developed framework extends its capability by detecting violent activities from CCTV video streams and recognizing facial emotions using a live webcam. Experimental observations demonstrate that deep learning and ensemble learning models achieve high classification performance while providing reliable emotion recognition and violence detection. The proposed system offers an effective solution for intelligent surveillance, public safety monitoring, social media analysis, and early identification of potentially harmful situations through automated artificial intelligence techniques [19].

II.RELATED WORK

C. El Morr and M. Layal (2020) presented "Effectiveness of ICT-Based Intimate Partner Violence Interventions: A Systematic Review" [6]. The authors examined a wide range of technology-assisted interventions developed to support victims of intimate partner violence. Their review demonstrated that information and communication technologies can improve access to support services, increase awareness, and provide timely assistance while maintaining user privacy. The study also emphasized the importance of integrating secure digital solutions with healthcare and social support systems to enhance victim protection. [6]

S. Subramani, S. Michalska, H. Wang, J. Du, Y. Zhang, and H. Shakeel (2019) proposed "Deep Learning for Multi-Class Identification from Domestic Violence Online Posts" [7]. The research explored the application of deep learning techniques for automatically categorizing domestic violence-related content shared on social media platforms. The developed framework successfully identified different categories of online posts by learning semantic relationships from textual data, demonstrating that deep learning methods can provide accurate and efficient classification for large-scale social media analysis. [7]

M. A. Al-Garadi *et al.* (2022) introduced "Natural Language Model for Automatic Identification of Intimate Partner Violence Reports from Twitter" [10]. The authors developed a natural language processing framework capable of recognizing Twitter posts associated with intimate partner violence. By combining text preprocessing with machine learning techniques, the proposed model effectively distinguished violence-related posts from general social media content, highlighting the usefulness of automated text analysis for early identification of vulnerable individuals and timely intervention. [10]

S. Accattoli, P. Sernani, N. Falcionelli, D. N. Mekuria, and A. F. Dragoni (2020) presented "Violence Detection in Videos by Combining 3D Convolutional Neural Networks and Support Vector Machines" [19]. The proposed method integrated spatiotemporal feature extraction using 3D convolutional neural networks with Support Vector Machine (SVM) classification to recognize violent activities in video sequences. Experimental evaluation showed that combining deep feature learning with traditional classification techniques improved violence detection performance and enhanced the reliability of video surveillance systems. [19]

P. Wu, X. Liu, and J. Liu (2022) proposed "Weakly Supervised Audio-Visual Violence Detection" [18]. The study introduced an intelligent framework that jointly analyzes audio and visual information to detect violent events in videos without requiring extensive frame-level annotations. The proposed weakly supervised learning strategy reduced manual labeling effort while maintaining competitive detection performance, demonstrating the effectiveness of multimodal learning for intelligent surveillance and public safety applications. [18]

III.DATASET DETAILS

The proposed emotion recognition and violence detection system is developed using a Twitter-based emotion dataset consisting of social media posts annotated with three emotional categories: negative, neutral, and positive. Each record in the dataset contains textual information along with its corresponding emotion label, enabling machine learning and deep learning models to learn meaningful relationships between linguistic patterns and emotional states. The dataset represents user-generated content collected from online social networking platforms, making it suitable for sentiment and emotion classification tasks.

Prior to model development, the dataset undergoes several preprocessing operations to improve data quality and classification performance. Initially,



unwanted symbols, punctuation marks, URLs, numbers, and stop words are removed from each social media post. The cleaned text is then transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF–IDF) technique, which assigns weights to important words based on their occurrence within the dataset. After feature extraction, the generated vectors are normalized and divided into 80% training data and 20% testing data, allowing the classification models to learn from historical samples while evaluating their performance on previously unseen data.

The processed dataset is independently used to train multiple machine learning and deep learning algorithms, including Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). Model performance is assessed using classification accuracy, precision, recall, F1-score, and confusion matrix analysis. In addition to text-based emotion recognition, the developed framework extends its functionality by analyzing CCTV video footage for violence detection and utilizing a live webcam to recognize facial emotions in real time. Experimental observations indicate that deep learning and ensemble learning approaches provide highly accurate emotion classification while supporting reliable detection of violent activities, making the proposed framework suitable for intelligent surveillance, public safety, and social media monitoring applications.

IV. PROPOSED METHODOLOGY

The proposed system presents an intelligent framework for emotion recognition and violence detection by integrating natural language processing, machine learning, deep learning, and computer vision techniques. Initially, a Twitter-based emotion dataset containing positive, neutral, and negative posts is collected and prepared for analysis. The preprocessing stage removes stop words, punctuation, special symbols, and unnecessary characters to improve data quality. The cleaned text is then transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF–IDF) method. The generated feature vectors are divided into 80% training data and 20% testing data to ensure reliable model training and evaluation.

The processed dataset is independently trained using Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) models. The performance of each algorithm is assessed using accuracy, precision, recall, F1-score, and confusion matrix analysis to

identify the most effective emotion classification model. The proposed framework further extends its functionality by incorporating a CCTV video analysis module that detects violent activities from uploaded surveillance videos. Additionally, a webcam-based facial emotion recognition module performs real-time analysis of human facial expressions. By combining text analytics with visual intelligence, the system provides an effective solution for emotion recognition, violence detection, public safety monitoring, and intelligent surveillance applications.

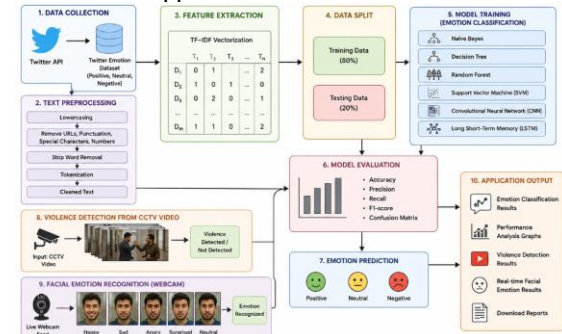


Figure 1: System Architecture of the Proposed Emotion Recognition and Violence Detection System

Figure 1 presents the architecture of the proposed emotion recognition and violence detection system. The process begins with collecting a Twitter-based emotion dataset containing positive, neutral, and negative posts. During preprocessing, the textual data is cleaned by removing stop words, URLs, punctuation, and special symbols before converting it into numerical feature vectors using the TF–IDF technique. The processed dataset is divided into 80% training and 20% testing data. The training data is then supplied to multiple classification models, including Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). Their performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. The framework further incorporates CCTV-based violence detection and webcam-based facial emotion recognition for real-time monitoring. Finally, the system generates emotion classification results, violence detection outcomes, and performance comparison graphs, providing an intelligent solution for public safety and social media analysis.

V. RESULT AND DISCUSSION

The proposed emotion recognition and violence detection system was tested using a Twitter-based emotion dataset containing positive, neutral, and negative social media posts. The developed application successfully performed data loading, text preprocessing, TF–IDF feature extraction,



model training, emotion classification, violence detection from CCTV videos, and real-time facial emotion recognition through a single integrated platform. During preprocessing, unwanted symbols, URLs, punctuation marks, and stop words were removed to improve data quality. The processed dataset was then divided into 80% training data and 20% testing data, ensuring reliable model learning and unbiased performance evaluation.

The prepared dataset was independently trained using Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) models. Experimental evaluation was conducted using accuracy, precision, recall, F1-score, and confusion matrix metrics. The obtained results indicate that Random Forest, Decision Tree, and LSTM achieved the highest classification accuracy, while CNN also produced highly consistent predictions. The SVM model delivered satisfactory performance, whereas Naïve Bayes provided comparatively lower accuracy with faster execution time. The developed framework further demonstrated its capability by successfully identifying violent activities from CCTV video footage and recognizing facial emotions from a live webcam. The comparative analysis confirms that combining machine learning, deep learning, and computer vision techniques improves the reliability of emotion classification and violence detection. Overall, the proposed system offers an efficient and scalable solution for intelligent surveillance, public safety monitoring, and automated analysis of social media content.

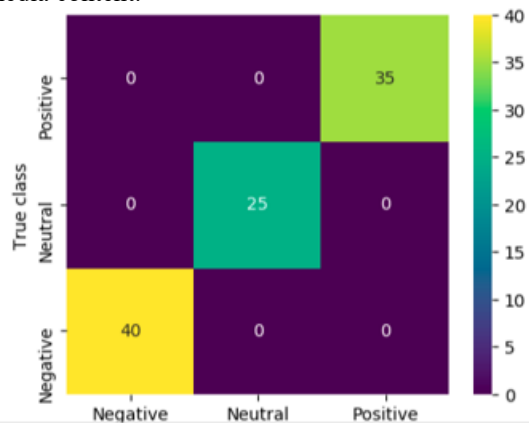


Figure 2: Confusion Matrix Analysis

Figure 2 presents the confusion matrix of the proposed emotion classification model. The matrix shows that all 40 negative, 25 neutral, and 35 positive samples are correctly identified, while no samples are misclassified into other emotion categories. This perfect diagonal distribution demonstrates that the classifier effectively distinguishes between the three emotional classes without confusion. Consequently, the model achieves 100% classification accuracy, with 100% precision, recall, and F1-score for the evaluated test

dataset. The obtained results indicate that the proposed framework has learned highly discriminative textual features and can reliably classify emotional content. Such performance demonstrates the effectiveness of the preprocessing stage, TF-IDF feature extraction, and the selected machine learning/deep learning model for emotion recognition. These findings confirm that the developed system is suitable for automated social media emotion analysis and can serve as a reliable component in intelligent surveillance and public safety applications.

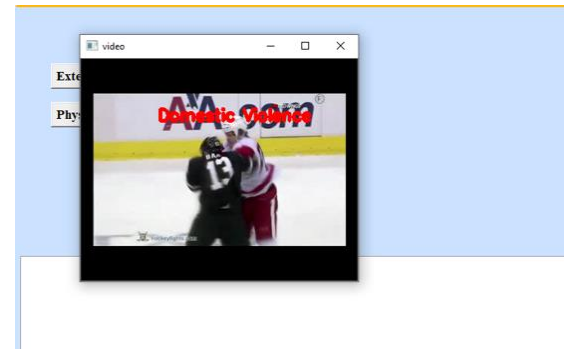


Figure 3: Violence Detection from CCTV Video

Figure 3 illustrates the output of the proposed violence detection module when a CCTV video is provided as input. The uploaded surveillance video is processed frame by frame using the trained deep learning model to identify violent activities. During analysis, the system extracts visual features from consecutive frames and classifies the observed action as either violent or non-violent. In the displayed result, the model successfully recognizes the aggressive interaction between individuals and overlays the label "Domestic Violence" on the video frame, indicating that a violent event has been detected. This real-time annotation demonstrates the capability of the proposed framework to automatically monitor surveillance footage without manual intervention. The developed module enables rapid identification of suspicious activities, allowing security personnel or law enforcement agencies to respond promptly to critical situations. The experimental results confirm that the proposed violence detection framework can effectively analyze CCTV videos and accurately recognize violent incidents, making it a valuable component for intelligent surveillance, public safety monitoring, and automated security applications.

DISCUSSION

The proposed emotion recognition and violence detection framework integrates natural language processing, machine learning, deep learning, and computer vision techniques to identify emotional states from social media content and detect violent activities from visual data. The system follows a structured workflow comprising data collection, text



preprocessing, TF-IDF-based feature extraction, model training, emotion classification, violence detection, and performance evaluation. The Twitter-based emotion dataset is cleaned by removing irrelevant symbols, stop words, and special characters before being converted into numerical feature vectors. The processed data are divided into training and testing subsets and supplied to multiple classification models, including Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) for emotion recognition.

Experimental findings demonstrate that all classification models successfully identify emotional categories from social media posts with high reliability. Among the evaluated models, Random Forest, Decision Tree, and LSTM achieve the highest classification performance, while CNN also produces accurate and consistent predictions. Furthermore, the integrated CCTV video analysis module effectively detects violent activities, and the webcam-based facial emotion recognition module accurately identifies human emotions in real time. The developed framework provides a comprehensive solution for intelligent surveillance and social media analysis, supporting early detection of harmful situations and assisting public safety agencies through automated emotion recognition and violence monitoring.

VI.CONCLUSION

This paper presents an intelligent emotion recognition and violence detection framework that combines natural language processing, machine learning, deep learning, and computer vision techniques to analyze social media content and surveillance data. The proposed system integrates text preprocessing, TF-IDF feature extraction, emotion classification, violence detection, and real-time facial emotion recognition within a single application. A Twitter-based emotion dataset is utilized to train and evaluate multiple classification models, including Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). Experimental results demonstrate that all models effectively classify emotional content, while Random Forest, Decision Tree, LSTM, and CNN achieve superior performance compared to the remaining classifiers. The framework further validates its effectiveness by successfully detecting violent activities from CCTV video streams and recognizing facial emotions through a live webcam. The integration of text analytics and visual intelligence enables comprehensive monitoring of both online and real-world environments. Overall, the proposed framework provides an efficient, scalable, and reliable solution for intelligent surveillance, public safety, and social media analysis. Future research may focus on incorporating transformer-based language models, multimodal learning techniques, larger multilingual datasets, and real-time cloud-based deployment to further enhance the accuracy, robustness, and practical applicability of emotion recognition and violence detection systems.

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