International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-13 Issue-10, September 2024

Hcnnxgboost: A Hybrid Cnn-Xgboost Approach for Effective Emotion Detection in Textual Data

Shivani Vora, Rupa G. Mehta

***Abstract:** in recent years, emotional analysis has become a key focus in computational studies, driven by the need to understand societal sentiments. this exploration is motivated by its many promising applications, such as community well-being evaluation, human-computer interaction, suicide prevention, and personalized recommendations. even with progress in other areas like identifying expressions from facial cues and speech, the study of text-based emotion recognition remains a fascinating field of research because machines struggle to interpret context, especially compared to human capabilities. our research addresses this by introducing a multiclass text-based emotion detection system that combines a cnn architecture with xgboost for improved classification in natural language processing. we pre-process publicly available datasets and use glove pre-trained word embeddings for better text representation. a major contribution of our work is enhancing the feature space by combining cnn probabilities with the original text data. the proposed hcnnxgboost model outperforms all other machine learning and deep learning algorithms across the emoint, isear, and crowdflower datasets, achieving f-scores of 90.1%, 87.4%, and 62.2%, respectively. experimental evaluations on benchmark datasets show better f-scores, confirming the effectiveness of our approach. comparisons with other classifiers highlight the enhanced performance and effectiveness of our hybrid cnnxgboost (hcnnxgboost) model, making it one of the best solutions for emotion classification in natural language processing tasks.*

***Keywords:** Emotion Recognition, Deep Learning, Convolution Neural Network, Extreme Gradient Boosting.*

I. INTRODUCTION

Information Technology is everywhere and has greatly changed our lives, allowing us to interact and be creative like never before. As technology advances, it makes daily tasks easier and helps meet our needs. For machines to do this, they must understand human behavior, especially emotions. Understanding and expressing emotions are crucial parts of human behavior and machines must deeply understand emotions to anticipate human needs [1]. Machines can identify human emotions through text, facial expressions, or speech.

Manuscript received on 28 July 2024 | Revised Manuscript received on 08 August 2024 | Manuscript Accepted on 15 September 2024 | Manuscript published on 30 September 2024.
*Correspondence Author(s)

Shivani Vora*, Department of Information Technology, C.K Pithawala College of Engineering and Technology, Surat (Gujarat), India. Email ID: shivani.vora@ckpcet.ac.in, ORCID ID: 0000-0003-2211-1548

Dr. Rupa G. Mehta, Department of Computer Science and Engineering, Sardar Vallabhbhai National Institute of Technology, Surat (Gujarat), India. Email ID: rgm@coed.svnit.ac.in

Various research streams focus on inferring emotions from different modes of communication, but text-based emotion recognition still requires more attention from researchers. Extracting emotions in textual data is difficult because of the absence of facial expressions and speech variations. This difficulty is further intensified by various factors such as the complexity of understanding context, the use of sarcasm, the inherent ambiguity of natural language, and the fast-evolving nature of Internet slang. Although significant strides have been made in the realms of speech and facial emotion recognition, text-based systems require more research to address these challenges and accurately interpret emotions in written communication. In recent years, the interest in emotion detection within the text has surged, given its vast potential applications in artificial intelligence, psychology, political science, suicide prevention, human-computer interaction, marketing, and community well-being assessment. Emotion detection from text involves identifying various categories of emotion, such as anger, joy, fear, and sadness. This can be accomplished through dictionary-based methods, machine learning, deep learning, or hybrid approaches. Studies have shown that dictionary-based rely on linguistic features like linguistic rules, ontologies, bag-of-words models, and dictionaries. In contrast, machine learning approaches employ algorithms such as logistic regression, Naive Bayes classifiers, support vector machines, and artificial neural networks. The scalability and domain customization limitations of lexicon-based methods can be addressed by machine learning approaches, which can also learn implicit emotional signals. Conventional machine learning techniques demand extensive feature extraction, while deep learning algorithms automatically learn conceptual features from data incrementally, eliminating the need for domain expertise and complex feature extraction. Recent studies show a growing use of deep learning and ensemble learning algorithms to improve the results of emotion detection tasks. Research shows that ensemble learning techniques create more generalizable models by combining several individual models [2][3][4]. Deep learning models with multiple layers are currently outperforming traditional models [5][6][7][8][9]. Deep ensemble learning combines the strengths of both deep learning and ensemble learning, resulting in models with better generalization performance [10]. The current studies show that an ensemble XGBoost algorithm is highly effective for text-based emotion detection due to its ability to handle high-dimensional data, manage class imbalance, and prevent overfitting [11]. Motivated by these recent studies, our research aims to propose a hybrid CNN with XGBoost (hCNNXGBoost) approach for effective emotion detection in English language text.

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

The key contributions of this research are as follows:

- Capturing rich feature sets to understand the lexical semantics for the classification of emotion using the CNN algorithm.
- Combining the CNN prediction as probabilities with original text data to augment feature space for improved emotion classification.
- Conduct experiments on different cutting-edge machine learning and deep learning techniques using three text-based datasets (EmoInt, ISEAR, and CrowdFlower (CF)).

The paper is structured as follows: Section 2 reviews previous works on CNN-based text classification, highlighting research gaps. Section 3 introduces the proposed hybrid CNNXGBoost approach and pre-processing techniques. Section 4 discusses empirical results and comparative analysis with existing systems. Section 5 concludes with future research directions and references.

II. RELATED WORK

Recently, approaches that employ deep learning and ensemble learning methods for emotion detection in text have been proposed. Deep learning methods utilize embedding vectors as input, which inherently convert syntactic and semantic information. Numerous data-driven approaches have been proposed for text-based classification, and CNN-based techniques have proven notably effective in text classification. CNNs have also shown promise in emotion recognition. Seo-Hui Park et al. employed CNNs to analyze tweets, achieving notable accuracy for certain emotions while struggling with others [12]. These findings underscore the complexities involved in accurately capturing the nuances of human emotions. Earlier, CNN-based text classification models proposed in [12][14] suffered from shallow architectures, limiting their ability to capture complex semantic features. Subsequent research [15] aimed to address these limitations by increasing model depth but encountered challenges in training, scalability, and generalizability. Later studies explored specific text domains such as short text, biomedical, and residential and introduced techniques like attention and multi-task learning [15][17]. However, these works often lacked comprehensive evaluation across diverse datasets and real-world applications. While significant progress has been made, the development of robust and scalable CNN-based text classification models for various domains remains an active area of research. The author of the work [2], proposed a BERT-based ensemble learning model for harmful news identification, achieving a 66.3% F1-score, though limited by dataset quality. The work by Kazmaier and Vuuren showcased the effectiveness of the ensemble approach in sentiment analysis, showing up to 5.53% performance improvements, but noted the computational challenges [3]. Briskilal developed an ensemble model using BERT and RoBERTa for classifying idioms and literal texts, achieving a 2% accuracy improvement, with limitations related to dataset size [4]. Motivated by these findings, our research proposes a hybrid CNN with XGBoost (hCNNXGBoost) approach for effective emotion detection in English text. The proposed methodology is described in the next section.

III. THE PROPOSED SYSTEM

This section introduces a novel hybrid approach for a text-based emotion detection system, integrating a CNN architecture with XGBoost (hCNNXGBoost) for improved multiclass classification tasks in Natural Language Processing. Our proposed model, hCNNXGBoost, is a CNN-based method for classifying text data. It uses pre-trained word embeddings and convolutional layers with ReLU activation to extract features. For classification, the model uses global pooling and fully connected layers, with the softmax function to determine class probabilities. Training is guided by sparse categorical cross-entropy loss. Once trained, the CNN model produced probability scores for each emotion class when making predictions on the test dataset. These probabilities were then incorporated as additional features, augmenting the original test dataset. The enhanced test dataset, now with probability features derived from the CNN, was used as input for the XGBoost classifier. This combination of components allows our model to achieve improved text classification across diverse multiclass datasets, including both balanced and imbalanced data.

A. Data Preparation

The data is prepared by applying several pre-processing techniques. These include replacing contraction words with their full forms, and numbers, removing punctuation, and URLs, and replacing line breaks and extra white spaces. Additionally, emoticons are replaced with appropriate words, and emojis in tweets are converted to text using the "emot" library in Python.

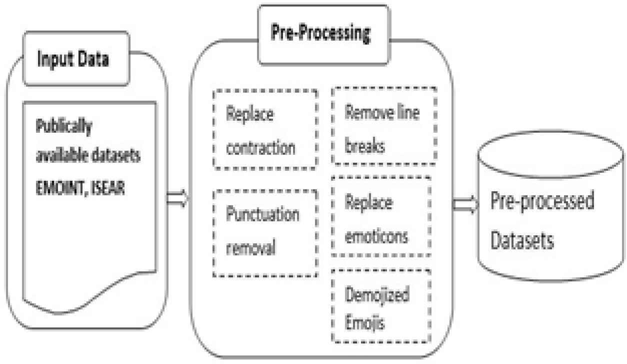

Fig.1: Pre-Processing Operations Performed on Datasets

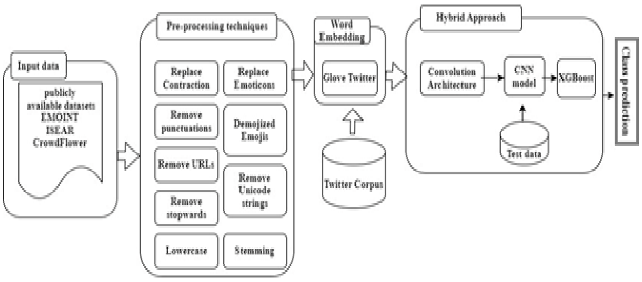

Fig.2: The Proposed Hybrid CNN with XGBoost

(hCNNXGBoost) model for text classification this demojization process helps to preserve the emotional information conveyed by emojis and emoticons in the text.

B. Model Preparation

We separately train the CNN deep learning model for multi-class classification tasks. We used a holdout validation dataset to validate base models. Predictions of base models are used to train an XGBoost ensemble classifier with default parameters given in Python's Scikit library.

- **Input Representation for CNN Model***:* The input to the CNN model is a sequence of words in the form of tokens. Each word is represented as a dense word vector, typically obtained using pre-trained word embeddings like GloVe. These word vectors form the basis of the input representation for the CNN model.
- **Convolution Layer:** The convolution layer in the CNN applies filters of different sizes to the input word embeddings. These filters slide over the input sequence and perform element-wise multiplications with local word vectors to extract local features. The convolution operation is mathematically represented as follows:

$$Conv\ (x) = \sum_{i=0}^{k-1}(x * w_i) + b_i \quad (1)$$

where x is the input sequence of word embeddings, w_i are the filter weights, and b_i is the bias term for the ith filter. The sum represents the result of applying the k filters to the input, producing feature maps.

- **ReLU Activation Layer***:* The Rectified Linear Unit (ReLU) [18] activation layer introduces non-linearity to the model. It applies the element-wise ReLU function to the output of the convolution layer, ensuring that only positive values are propagated to the next layer while setting negative values to zero. The ReLU activation function is defined as:

$$ReLU\ (x) = \max(0, x) \quad (2)$$

- **Classification***:* Following ReLU activation, the features undergo pooling to obtain global text representations. These pooled features are then fed to a fully connected layer with softmax activation, which assigns probabilities to each class label. Additionally, a dropout layer [19] is implemented between the hidden layer and output layer, randomly enabling or disabling connections (setting some to 0) among hidden units during each training phase update.

This helps in mitigating overfitting. The sparse categorical cross-entropy loss function [20] is used for training.

$$LOSS = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i}, c\ log\ (p_i, c) \quad (3)$$

where N is the number of samples in the batch, C is the number of classes, $y_{i,c}$ is the binary indicator (0 or 1) for the true class label of sample i, and $p_{i,c}$ is the predicted probability of sample i belonging to class c.

- **Extreme Gradient Boosting (XGBoost) Classifier:** XGBoost leverages the probabilities obtained from the CNN, transformed by the fully connected layer, as additional features to inform the classification process. XGBoost is highly effective for text-based emotion detection due to its ability to handle high-dimensional data from text vectorization methods. It also offers built-in mechanisms to handle class imbalance and prevent overfitting through regularization. Additionally, XGBoost can manage non-linear relationships in data through kernel functions, providing flexibility in capturing complex patterns in text data [11]. The architecture of the proposed hCNNXGBoost model is illustrated in Fig. 2. The model trains and tunes the CNN deep learning model using pre-trained GloVe word embeddings, which are based on 2 billion tweets, comprising 27 billion tokens and a vocabulary of 1.2 million words [21]. In our CNN model, we employ a convolutional layer followed by max-pooling (conv-pool).

Table-I: Various Hyperparameters for Training of The CNN Model

Parameter	Values for Each Text-based Dataset
Loss	Cross-Entropy
Hidden Activations	ReLU [18]
Output Activations	Softmax [22]
Shared Layers	CNN – 1D (conv-pool)
Fully-connected Layer	64 neurons, L2 regularization
Convolution Filters	Filters-512 Filter sizes-(2), (2,3,4) and (3,4,5)
Batch	64
Epochs	51 (with checkpoint option)
Dropout [19]	25%
Optimizer	Adam [23]

The convolutional layer includes 64 filters that slide over 2-word sequences. This is followed by a fully connected layer with 64 nodes and an output layer. The number of neurons in the output layer matches the number of classes in the dataset. The fully connected layer uses the ReLU activation function [17], and L2 regularization is applied as the loss function. For classification, the output layer employs the softmax activation function [22]. To enhance regularization, we apply a 25% dropout [19] in the fully connected layer. Adam optimizer [23] with default parameters is utilized for gradient-based training. A detail of hyperparameters for training of the CNN deep neural network is present in Table 1. The selection of hyper-parameters for the CNN model was obtained by using the "Hyperopt" hyper-parameter optimization algorithm [24][35][36][37]. Hyperparameter optimization is the process aimed at identifying the optimal combination of hyperparameter values to achieve maximal performance within a reasonable amount of time. It significantly influences the predictive accuracy of a machine learning algorithm. Hyperopt, a powerful Python library, uses a technique called Bayesian optimization to fine-tune parameters. The number of trees used in XGBoost was set to 25. The XGBoost algorithm was utilized from the "xgboost" library.

C. Datasets

We evaluated our proposed model using five benchmark datasets: EmoInt, ISEAR, and CrowdFlower (CF). The details of all three datasets are depicted in Table 2.

- **EmoInt Dataset:** This dataset, from the WASSA-2017, shared task [25], contains tweets representing four emotions (anger, fear, joy, sadness) with intensity scores. It includes 3,613 training tweets, 347 validation tweets, and 3,142 test tweets.
- **ISEAR Dataset:** Collected through questionnaires from individuals of various cultural backgrounds, this dataset contains 7,666 sentences expressing seven emotions (anger, disgust, fear, sadness, shame, joy, guilt) [26]. We divided the data into 80% for training, 10% for validation, and 10% for testing.
- **CrowdFlower Dataset:** The dataset is significantly imbalanced across the emotion categories, with varying tweet counts [27].

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

For experiments, we take proportionate stratified samples from the CrowdFlower (CF) dataset. Here the fraction of the sampling size used is 0.3. We used 11,977 proportionate stratified samples with an 80-10-10 split for training, validation, and testing.

Table- II: Details of the used Experimental Datasets

Datasets	Type of Class	# Classes	Train	Val	Test	Total
EmoInt[1]	Balanced	4	3,613	347	3,142	7,102
ISEAR[2]	Balanced	7	6132	307	1227	7,666
CF[3]	Imbalanced	13	9581	480	1916	11977

[1]https://aclanthology.org/W17-5207
[2]http://www.affective-sciences.org/researchmaterial
[3]https://www.kaggle.com/c/crowdflowersearch-relevance/overview

IV. RESULTS AND DISCUSSION

To thoroughly evaluate the proposed hybrid CNNXGBoost model, we utilized six different machine learning techniques: Logistic Regression (LR), Support Vector Machine (SVM), Multinomial Naive Bayes, Random Forest (RF), XGBoost, and Artificial Neural Network (ANN). Given that CNN is a deep learning architecture based on convolutional neural networks, for comparison of their performance, we incorporated some deep learning techniques. The aforementioned algorithms were developed using the Python-based Scikit-learn library, with some parameter modifications.In Logistic Regression (LR) for multiclass classification, we set the parameter multiclass as "multinomial". The number of trees used in Random Forest and XGBoost was set to 25. The XGBoost algorithm was utilized from the "xgboost" library. Specifically, we implemented bidirectional LSTM (BiLSTM), bidirectional GRU (BiGRU), and RCNN. We performed experiments with TextCNN using different filter sizes for convolution operations and conducted results. The Python-based Keras library was used for the implementation of ANN and deep learning models. The hyperparameters of the deep learning-based models are optimized through the Hyperopt algorithm. For evaluation, we computed the f-score for the classification of emotions. We analyzed CNN architectures with filter sizes of 2, mixed 2-3-4, and mixed 3-4-5. Table 3 illustrates the results. The single filter size of 2 performed best on the ISEAR and CrowdFlower datasets and showed comparable performance on the EmoInt dataset, making it the more suitable choice overall. We implemented the CNN model with various linear and nonlinear classifiers. Results are presented in Table 4. The result shows the f-score performance of CNN with linear and nonlinear classifiers such as Logistic regression and SVM on EmoInt, ISEAR, and CF datasets. XGBoost improves f-scores by an average of 22.32% over LR and 26.00% over SVM, highlighting its better performance in emotion detection tasks. and making it the best choice for text classification. We tested the XGBoost classifier with 5 to 100 trees and found optimal performance with 20 to 25 trees. We chose 25 trees for the best balance of accuracy and efficiency. To strengthen the credibility of our proposed approach, we conducted a thorough evaluation using state-of-the-art machine learning and deep learning algorithms. Table 5 presents a comparative analysis of proposed model results compared to leading algorithms.

Table- III: Comparisons of the Performance of Variants of CNN Models on Datasets

Model	f-score (%)		
variants of 1D convolution layers	EmoInt	ISEAR	CF
single filter size of 2	84.91	57.37	31.66
combination of (2, 3, 4) filter sizes	84.72	56.47	34.11
combination of (3, 4, 5) filter sizes	84.91	51.34	31.71

Table- IV: Results of the CNN Model with Different Classifiers on four Datasets

Model	f-score (%)		
CNN with different classifiers	EmoInt	ISEAR	CF
CNN with LR	83.80	61.04	27.90
CNN with SVM	60.72	62.3	36.67
CNN with XGBoost	90.1	87.4	62.2

The results show that the proposed hCNNXGBoost model outperforms all other machine and deep learning algorithms across the EmoInt, ISEAR, and CrowdFlower datasets, achieving f-scores of 90.1%, 87.4%, and 62.2%, respectively. Conventional machine learning models like Multinomial NB, LR, and SVM have lower f-scores, ranging from 27.40% to 78.87%. Random Forest and XGBoost show moderate performance, with f-scores between 31.66% and 80.99%. Among DL models, CNN performs well on EmoInt (85.2%) and ISEAR (60.2%) but less so on CrowdFlower (33.89%). Other DL models, such as BiGRU, BiLSTM, and RCNN, have variable f-scores from 28.15% to 83.64%. The hCNNXGBoost's consistently improved performance highlights its robust architecture, effectively combining convolutional and gradient-boosting techniques to handle the complexities of multi-class emotion classification. The visual representation is depicted in Figure 3.

A. Comparative Analysis

We compare our proposed hCNNXGBoost system to the existing methodologies to further justify our work. Comparison of the existing approaches with the proposed approach for EmoInt, ISEAR, and CrowdFlower (CF) emotion datasets (refer to Table 6). Results show that, among the mentioned systems, the proposed hCNNXGBoost model performs accurately on all three emotion datasets and demonstrates remarkable effectiveness in emotion detection tasks.

V. CONCLUSION AND FUTURE SCOPE

This study introduces a hybrid CNN with an XGBoost model, adept at multiclass emotion detection in natural language processing.

Table- V: Results of the Proposed hCNNXGBoost Approach Against Other Algorithms

Model	f1-score (%)		
	EmoInt	ISEAR	CF
Naïve Bayes (NB)	72.15	56.8	27.4
Logistic regression (LR)	78.87	56.64	31.66
Support Vector Machine (SVM)	69.41	50.53	30.57
Random Forest (RF)	80.9	50.53	31.66
XGBoost (XGB)	80.99	53.46	32.25
Artificial Neural Network (ANN)	75.14	51.75	23.06
Bidirectional GRU (BiGRU)	83.64	47.84	28.82
Bidirectional LSTM (BiLSTM)	83.32	47.02	28.15
Convolution Neural Network (CNN)	85.2	60.2	33.89
Recurrent Convolutional Neural Network (RCNN)	82.2	56.64	29.32
The proposed hCNNXGBoost	90.1	87.4	62.2

Through rigorous experimentation across various datasets, our approach showcases improved f-scores, notably better comparing other models, confirming its efficacy. The model was tested across diverse datasets, handling imbalanced datasets with varying class distributions, showcasing its adeptness in emotion-centric tasks. The fusion of CNN probabilities with original text data enriches the feature space, improving precise emotion classification. Future extensions could include multilingual and multilabel emotion detection, alongside addressing interpretability and bias within the hybrid model for practical applications.

Table- VI: Comparison of the Proposed Model against Existing Approaches in All Datasets

Dataset	Study	Technique	Result f-score (%)
EmoInt	Akhtar et al. (2022) [28]	Multi-task Ensemble (CNN, LSTM, GRU)	89.3
	Bostan & Klinger (2018) [29]	Corpus Analysis	88
	The Proposed hCNNXGBoost	CNN combined with the XGBoost algorithm	90.1
ISEAR	Felbo et al. (2017) [30]	DeepMoji model consists of LSTM	57
	Bostan et al. (2018) [29]	maximum entropy classifiers using Bag of Word features	60.5
	Kratzwald et al. (2018) [31]	Sent2affect transfer learning technique and BiLSTM model	59.6
	Batbaatar et al. (2019) [32]	SENN model with BiLSTM and CNN	74.6
	Rei and Mladenić (2023) [33]	Language models (RoBERTa) with zero-shot transfer	76
		Language models (RoBERTa) with few shot transfer	62
	The Proposed hCNNXGBoost	CNN combined with the XGBoost algorithm	87.4
CF	Y. Oscar (2020) [34]	Ensemble Neural Network (CNN, RNN, Pooling)	38
	The Proposed hCNNXGBoost	CNN combined with the XGBoost algorithm	62.2

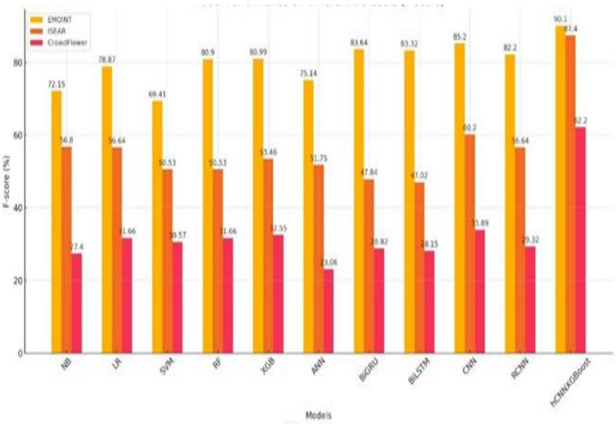

Fig.3: Comparison of Algorithm Performance Across Three Datasets

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is attributed equally to all participating authors.

REFERENCES

1. Chatterjee, A., Gupta, U., Chinnakotla, M. K., Srikanth, R., Galley, M. & Agrawal, P. Understanding emotions in text using deep learning and big data. Comput. Hum. Behav. 93, 309-317 (2019). https://doi.org/10.1016/j.chb.2018.12.029
2. Lin, S. Y., Kung, Y. C. & Leu, F. Y. Predictive intelligence in harmful news identification by BERT-based ensemble learning model with text sentiment analysis. Inf. Process. Manage. 59, 102872 (2022). https://doi.org/10.1016/j.ipm.2022.102872
3. Kazmaier, J. & Vuuren, J. H. v. The power of ensemble learning in sentiment analysis. Expert Syst. Appl. 187, 115819 (2022). https://doi.org/10.1016/j.eswa.2021.115819 https://doi.org/10.1016/j.eswa.2021.115819
4. Briskilal, J. & Subalalitha, C. N. An ensemble model for classifying idioms and literal texts using BERT and RoBERTa. Inf. Process. Manage. 59, 102756 (2022). https://doi.org/10.1016/j.ipm.2021.102756 https://doi.org/10.1016/j.ipm.2021.102756
5. Li, C., Bao, Z., Li, L. & Zhao, Z. Exploring temporal representations by leveraging attention-based bidirectional LSTM-RNNs for multi-modal emotion recognition. Inf. Process. Manage. 57, 102185 (2020). https://doi.org/10.1016/j.ipm.2019.102185
6. Colnerič, N. & Demšar, J. Emotion recognition on Twitter: Comparative study and training a unison model. IEEE Trans. Affect. Comput. 11, 433-446 (2020). https://doi.org/10.1109/TAFFC.2018.2807817
7. Bharti, S. K., Varadhaganapathy, S., Gupta, R. K., Shukla, P. K., Bouye, M., Hingaa, S. K. & Mahmoud, A. Text-based emotion recognition using deep learning approach. Comput. Intell. Neurosci. 2022, 2645381 (2022). https://doi.org/10.1155/2022/2645381 https://doi.org/10.1155/2022/2645381

8. Hung, J. C., Lin, K. C. & Lai, N. X. Recognizing learning emotion based on convolutional neural networks and transfer learning. Appl. Soft Comput. 84, 105724 (2019). https://doi.org/10.1016/j.asoc.2019.105724 https://doi.org/10.1016/j.asoc.2019.105724
9. Behera, R. K., Jena, M., Rath, S. K. & Misra, S. Co-LSTM: Convolutional LSTM model for sentiment analysis in social big data. Inf. Process. Manage. 58, 102435 (2021). https://doi.org/10.1016/j.ipm.2020.102435
10. Vora, S. & Mehta, R. G. HDEL: A hierarchical deep ensemble approach for text-based emotion detection. Multimed. Tools Appl. (2024). https://doi.org/10.1007/s11042-024-19032-y https://doi.org/10.1007/s11042-024-19032-y
11. Ghosal, S. & Jain, A. Depression and suicide risk detection on social media using fasttext embedding and XGBoost classifier. Procedia Comput. Sci. 218, 1631-1639 (2023). https://doi.org/10.1016/j.procs.2023.01.141
12. Park, S. H., Bae, B. C. & Cheong, Y. G. Emotion recognition from text stories using an emotion embedding model. In 2020 IEEE International Conference on Big Data and Smart Computing (BigComp), 2020. https://doi.org/10.1109/BigComp48618.2020.00014
13. Kalchbrenner, N., Grefenstette, E. & Blunsom, P. A convolutional neural network for modeling sentences. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics, 655–665 (2014). https://doi.org/10.3115/v1/P14-1062
14. Kim, Y. Convolutional neural networks for sentence classification. In Proc. Conf. Empirical Methods in Natural Language Processing, 1746–1751 (2014). https://doi.org/10.3115/v1/D14-1181
15. Duque, A. B., Santos, L. J., Macedo, D. & Zanchettin, C. Squeezed very deep convolutional neural networks for text classification. In International Conference on Artificial Neural Networks, 193–207 (Springer, 2019). https://doi.org/10.1007/978-3-030-30487-4_16
16. Ibrahim, M. A., Khan, M. U. G., Mehmood, F., Asim, M. N. & Mahmood, W. Ghs-net: A generic hybridized shallow neural network for multi-label biomedical text classification. J. Biomed. Inform. 116, 103699 (2021). https://doi.org/10.1016/j.jbi.2021.103699
17. Yang, D. U., Kim, B., Lee, S. H., Ahn, Y. H. & Kim, H. Y. Autodefect defect text classification in residential buildings using a multi-task channel attention network. Sustain. Cities Soc. 103803 (2022). https://doi.org/10.1016/j.scs.2022.103803
18. Glorot, X., Bordes, A. & Bengio, Y. Deep sparse rectifier neural networks. In Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, 315-323 (2011).
19. Srivastava, N. et al. Dropout: A simple way to prevent neural networks from overfitting. J. Mach. Learn. Res. 15, 1929-1958 (2014).
20. Botev, Z. I., Kroese, D. P., Rubinstein, R. Y. & L'Ecuyer, P. The cross-entropy method for optimization. In Handbook of Statistics, 31, 35-59 (2013). https://doi.org/10.1016/B978-0-444-53859-8.00003-5
21. Pennington, J., Socher, R. & Manning, C. GloVe: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), 1532–1543 (2014). https://doi.org/10.3115/v1/D14-1162
22. Goodfellow, I., Bengio, Y. & Courville, A. 6.2. 2.3 softmax units for multinoulli output distributions. Deep Learning, 180 (2016).
23. Kingma, D. P. & Ba, J. Adam: A method for stochastic optimization. CoRR abs/1412.6980 (2014).
24. Bergstra, J., Yamins, D. & Cox, D. D. Making a science of model search: Hyperparameter optimization in hundreds of dimensions for vision architectures. In Proceedings of the 30th International Conference on International Conference on Machine Learning - Volume 28, 115–123 (JMLR.org, 2013).
25. Mohammad, S., Bravo-Marquez, F., Salameh, M. & Kiritchenko, S. SemEval-2018 task 1: Affect in tweets. In Proceedings of the 12th International Workshop on Semantic Evaluation, 1–17 (2018). https://doi.org/10.18653/v1/S18-1001
26. Wallbott, H. G. & Scherer, K. R. How universal and specific is emotional experience? Evidence from 27 countries on five continents. Soc. Sci. Inf. 25, 763–795 (1986). https://doi.org/10.1177/053901886025004001
27. CrowdFlower. Sentiment Analysis: Emotion in Text (2016). https://doi.org/10.1109/TAFFC.2019.2926724
28. Akhtar, M. S., Ghosal, D., Ekbal, A., Bhattacharyya, P. & Kurohashi, S. All-in-One: Emotion, sentiment and intensity prediction using a multi-task ensemble framework. IEEE Trans. Affect. Comput. 13, 285-297 (2022). https://doi.org/10.1109/TAFFC.2019.2926724
29. Bostan, L. A. M. & Klinger, R. An analysis of annotated corpora for emotion classification in text. In Proceedings of the 27th International Conference on Computational Linguistics, 2104–2119 (2018).
30. Felbo, B., Mislove, A., Søgaard, A., Rahwan, I. & Lehmann, S. Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion, and sarcasm. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, 1615–1625 (Assoc. Comput. Linguist., 2017). https://doi.org/10.18653/v1/D17-1169
31. Kratzwald, B., Ilić, S., Kraus, M., Feuerriegel, S. & Prendinger, H. Deep learning for affective computing: Text-based emotion recognition in decision support. Decis. Support Syst. 115, 24–35 (2018). https://doi.org/10.1016/j.dss.2018.09.002
32. Batbaatar, E., Li, M. & Ryu, K. Semantic-emotion neural network for emotion recognition from text. IEEE Access 7, 111866–111878 (2019). https://doi.org/10.1109/ACCESS.2019.2934529
33. Rei, L. & Mladenić, D. Detecting fine-grained emotions in literature. Appl. Sci. 13, 7502 (2023). https://doi.org/10.3390/app13137502
34. Youngquist, O. An ensemble neural network for the emotional classification of text. In the Thirty-Third International Flairs Conference (2020).
35. Reddy, M. V. K., & Pradeep, Dr. S. (2021). Envision Foundational of Convolution Neural Network. In International Journal of Innovative Technology and Exploring Engineering (Vol. 10, Issue 6, pp. 54–60). https://doi.org/10.35940/ijitee.f8804.0410621
36. Kumar, P., & Rawat, S. (2019). Implementing Convolutional Neural Networks for Simple Image Classification. In International Journal of Engineering and Advanced Technology (Vol. 9, Issue 2, pp. 3616–3619). https://doi.org/10.35940/ijeat.b3279.129219
37. Priyatharshini, Dr. R., Ram. A.S, A., Sundar, R. S., & Nirmal, G. N. (2019). Real-Time Object Recognition using Region based Convolution Neural Network and Recursive Neural Network. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 8, Issue 4, pp. 2813–2818). https://doi.org/10.35940/ijrte.d8326.118419

AUTHORS PROFILE

Shivani Vora is an Assistant Professor in the Department of Information Technology, C.K Pithawala College of Engineering and Technology (CKPCET), Surat and PhD Research Scholar at Sardar Vallabhbhai National Institute of Technology (SVNIT), Surat, India. She has completed her M.Tech (Research) in Computer Engineering from Sardar Vallabhbhai National Institute of Technology, Surat. The author has several years of experience in teaching and research, also published many papers in reputed international journals and conferences. Her area of research includes Data Mining, Machine Learning, Natural Language Processing, Artificial Intelligence, and Fuzzy Classification Discretization. etc. She is guiding several UG and PG Students at her Institute.

Dr. Rupa Mehta is a Professor in the Department of Computer Science and Engineering at the National Institute of Technology (SVNIT), Surat. She has completed her M.Tech (Research) and Ph.D. in Computer Engineering from Sardar Vallabhbhai National Institute of Technology, Surat. With several years of experience in teaching and research, she has published numerous papers in reputed international journals and conferences. Her areas of research include Data Mining, Machine Learning, Natural Language Processing, Artificial Intelligence, Database Management Systems, Advanced Data Structures, Big Data Analytics, and Fuzzy Classification Discretization. She guides several undergraduate and postgraduate students and has also supervised Ph.D. scholars at her institute.