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An NLP-Driven Approach to Improved Emotion Recognition in Textual Data Utilizing the Yelp Dataset

Homa Rizvi[1], Farheen Siddiqui[2], Dr. Nikhat Akhtar[3], Shamim Ahmad[4], Dr. Yusuf Perwej[5]

[1]Assistant Professor, Department of Computer Science & Engineering, Shri Ramswaroop Memorial University, Deva Road, Lucknow
[2]Assistant Professor, Department of Computer Science & Engineering, Shri Ramswaroop Memorial University, Deva Road, Lucknow
[3]Associate Professor, Department of Computer Science & Engineering, Goel Institute of Technology & Management, Lucknow
[4]Assistant Professor, Department of Computer Science & Information System, Shri Ramswaroop Memorial University, Deva Road, Lucknow
[5]Professor, Department of Computer Science & Engineering, Shri Ramswaroop Memorial University, Deva Road, Lucknow

Abstract: The increasing impact of artificial intelligence in natural language processing (NLP) has rendered emotion identification from textual data an essential element in applications including sentiment analysis, customer feedback assessment, mental health evaluation, and human-computer interaction. Social networking platforms have become a vital medium for expressing emotions globally owing to the fast proliferation of the Internet age. Numerous individuals use written information, images, audio, and video to convey their emotions or perspectives. Conversely, text communication via web-based networking platforms is quite overwhelming. A substantial volume of unstructured data is produced on the Internet every second as a result of social media platforms. The data must be analyzed as swiftly as it is created to understand human psychology, achievable via sentiment analysis, which identifies polarity in words. Conventional models often fail to accurately represent the complex semantic relationships and emotional nuances inherent in textual and emoji communication. Our strategy utilizes BERT's capacity to store profound contextual links and BiLSTM's proficiency in modeling sequential patterns, therefore improving emotion identification accuracy. We evaluate our approach using two reputable benchmark Yelp datasets, which constitute a substantial text emotion identification corpus of 30,000 phrases. The text-based Yelp dataset allows the model to acquire intricate linguistic patterns and emotional signals inherent in written language. By incorporating these varied modalities, our method promotes a more thorough and flexible emotion categorization system. The integration of contextual embeddings and sequential learning significantly enhances robustness, making emotion recognition more accurate and dependable.

Keywords: Emotion Recognition, Feature Extraction, Long Short-Term Memory (LSTM), BERT, Deep Learning, NLP, BiLSTM, Sentiment Analysis, Yelp Dataset.

1. Introduction

There is a growing need to comprehend not just the content of people's words but also the emotions conveyed by them in the digital realm. Emotion detection is the name of this solution; it is an interesting subfield of NLP [1] that is growing in importance in many fields. However, single-model models still struggle to grasp nuanced emotional variations, especially in cases involving sarcasm, mixed emotions, or changes in domain-specific sentiment, despite their enhanced contextual awareness. We provide an ensemble learning approach that combines a BiLSTM [3] classifier with BERT-based feature extraction [2] to circumvent these restrictions. If you combine BERT with BiLSTM, you get the greatest of both worlds: BERT's contextual embeddings are extensive, while BiLSTM's sequential dependencies are crucial for textual emotion transition comprehension [4]. Our methodology enhances predictions and mitigates misclassification errors using ensemble approaches such as stacking, majority voting, or weighted averaging. By combining the two approaches, we find that it is more versatile, boosts generalization by preventing overfitting, and more resilient overall [5]. Additionally, we explore ways to enhance emotion detection via the integration of attention processes and numerous emotion-specific submodels. Healthcare for mental health assessment, consumer review analysis, and social media [7] content filtering are just a few examples of the many areas that might benefit from our scalable architecture [6]. Our ensemble learning [8] approach is a strong contender for practical emotion detection applications, as shown by experimental comparisons on benchmark datasets. It outperforms a single model in terms of accuracy, F1-score, and resilience. Both educators and students benefit greatly from sentiment [9] and emotion analysis in the classroom. Not only do a teacher's academic qualifications matter, but so do his passion, skill, and commitment to his students. The best way for a teacher to enhance their teaching methods is to take timely student feedback.

2. Background

From simple lexicon-based methods to complex deep learning models, emotion detection in text has come a long way. To classify emotions, researchers first relied on lexicons that were hand-crafted [10]. After that, text characteristics were used by machine learning models to categorize the text. Phrasal verbs were the primary focus of the emotion identification work done by Seal et al. [11] using a keyword-based technique. The data was pre-processed using ISEAR [13] data, and the keyword-based technique was then used. After coming across several phrasal verbs that ought to be linked to emotion categories but weren't, they proceeded to construct their own database. This used their database to classify phrasal verbs and terms that are synonymous with different emotions [14]. While this did improve accuracy to 65%, it failed to solve the researcher's previous problems, such as an inadequate set of emotion keywords and an ignoring of word semantics in meaning [15]. A technique for encoding emotional meanings into vector form has been presented in [12] and is called Emo2Vec. Using a multitask learning architecture, Emo2Vec was trained using both smaller and bigger datasets. The former included datasets like ISEAR, WASSA, and Olympic, while the latter included datasets like Olympic. It demonstrates that their outcomes outperform those of DeepMoji embedding, Convolution Neural Networks (CNNs) [17], and others. have put their expertise in areas such as stress detection, mood analysis, and sarcasm classification to use. At last, the model Emo2Vec can outperform the competition when paired with Logistic Regression and GloVe. In their study, Ragheb et al. Using a learning-based technique, W. Ragheb et al. [18] attempted to identify emotions in textual discussions.

In order to detect hate speech on social media, Rodriguez et al. [18] use emotion analysis. Finding and analysing the unstructured data [19] of chosen social media postings with the intent to promote hatred in the comment sections was their goal with this study. In their evaluation of emotional content in textual data, Cao et al. [20] used machine learning and deep learning techniques. The difficulties and problems with emotion recognition in text are further brought to light by this. Both the explicit location of context in an opinionated phrase and the presence of many aspects with varying polarity inside a single sentence were addressed by Ma et al. [22] in relation to aspect-level analysis. To address these concerns, the authors developed a two-stage model using LSTM [23]v, which includes an attention mechanism. They came up with this approach on the premise that words in the context close to the aspect are more important and need more attention than words farther out in the context. Stage one involves the model using a position attention mechanism to exploit various parts of a text one by one. The second stage involves finding pairings of aspects and sentences based on their relative positions and surrounding context, and concurrently determining the polarity of each team [24].

Understanding the user's feelings has become absolutely critical for business or organization. One way to find out whether someone has a favourable or negative attitude on a topic is to utilize sentiment analysis, which is also called opinion mining. The goal of sentiment analysis is to identify the writer's intended tone, which might be positive, negative, or neutral, by extracting relevant information and semantics from texts utilizing natural processing methods [22]. The dataset's class range included in sentiment analysis is not limited to only positive or negative; it may also be agreed or disagreed, good or poor, as the aim of sentiment analysis is to detect polarity and categorize opinionated words as positive or negative [25]. As an additional metric, it may be measured using a 5-point scale: very disagree, not at all agree, neutral, agree, or very agree [26]. In order to identify emotions in user-generated material, the authors investigated deep learning methods, namely CNNs [27] and LSTM networks. The efficacy of merging these models in capturing textual contextual subtleties was shown in their study [28]. Models such as BERT and LSTM were utilized for emotion categorization in this study, which cantered on transfer learning methodologies. The research shown that using pre-trained language models may significantly enhance performance on tasks involving emotion identification.

3. Dataset

This particular dataset is a subset of the companies, reviews, and user data that Yelp provides. It was first developed for the purpose of participating in the Yelp Dataset Challenge, which provides students with the opportunity to do research or analysis on Yelp's data and then submit their findings [29]. A total of eight metropolitan regions in the United States of America and Canada are included in the most current dataset, which contains information about enterprises. Among the five JSON files that make up this dataset. The Yelp Open Dataset is a subset of the Yelp data that is being made available for use in educational settings. The information it gives is based on real-world information about companies, such as reviews, images, check-ins, and qualities such as hours of operation, parking availability, and atmosphere.

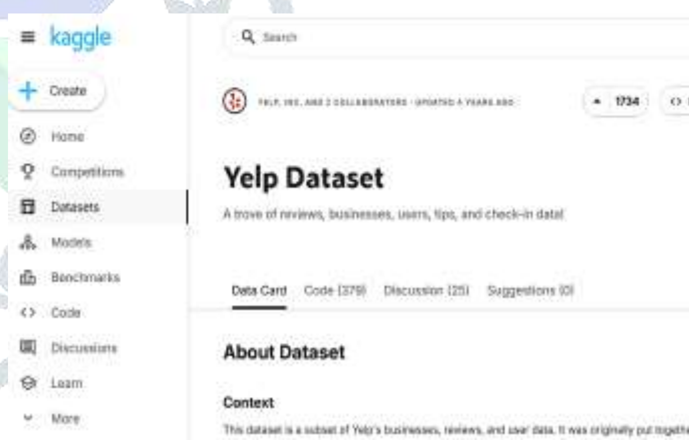

Figure 1: The Yelp Dataset

4. The Proposed System

We introduce an ensemble deep learning model that merges BERT and BiLSTM in this research to enhance NLP. Improving sequential learning and contextual representation are the goals of the proposed approach, which builds upon the MEDA framework. In contrast to BiLSTM's utilization of bidirectional recurrence to improve long-range interdependence, BERT captures deep semantic meaning via self-attention techniques. By fusing these designs, our model is able to generalize across different natural language processing tasks and attain better accuracy [30]. Compared to state-of-the-art methods, our hybrid architecture achieves better results in emotion detection experiments when measuring recall, accuracy, and overall resilience. Together, sequential learning and transformer-based embeddings improve text understanding and categorization, as shown in the findings [31]. Here are the stages that make up the text categorization pipeline. Classification begins with raw text data. tokenization and pre-processing: this phase involve normalizing the case of the text, stripping punctuation, and removing stop words, among other chores. Thirdly, a BERT encoder is used to create contextualized word embeddings. This is achieved by encoding bidirectional dependencies, which are introduced into the pre-processed text [32]. item Improving the Embedding Layer, additional modifications are applied to the embeddings in order to improve the representation of features. Fourthly, the BiLSTM Layer processes the embeddings in order to determine the forward and backward context dependencies sequentially. A classification layer receives the output of BiLSTM and decides if classification is to be performed [33]. If classification is completed, the output is generated. If classification is skipped, the system either stops or goes back to the beginning for further processing. This is the sixth branch of the decision-making process.

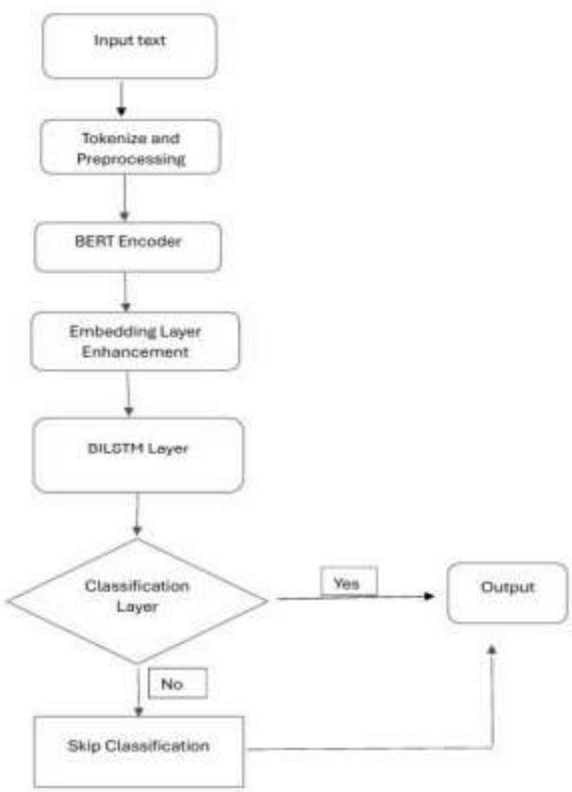

Figure 2: The Proposed System

For the purpose of extracting deep context from text data, BERT is a state-of-the-art language representation model. Word2Vec and GloVe are two of the most popular word embeddings [34], while BERT uses a bidirectional transformer model, which allows it to understand words in context rather than just their left-to-right or right-to-left dependencies [35]. With its extensive training on huge corpora, BERT is very effective for natural language processing (NLP) applications like emotion identification since it generates contextual embeddings via domain-specific task tailoring.

To implement our proposed method, we train BERT to extract rich semantic characteristics from the Yelp text dataset. Multiple layers of transformers are given an input phrase after it has been tokenized and divided into subword units using WordPiece embeddings [36]. Our categorization algorithm is fed the whole phrase by means of the last concealed state of the [CLS] token. Utilizing BERT's profound understanding of context, we enhance the precision of emotion classification and successfully capture nuanced expressions of emotion in the text Yelp dataset.

By extending LSTM, BiLSTM is able to understand both forward and backward dependencies [37]. BiLSTM is very helpful in emotion detection tasks because it helps to increase LSTMs' effective capacity to maintain long-range reliance by processing input sequences in both directions. Following the extraction of contextual embedding from BERT, we include a BiLSTM layer into our system [38]. After BERT generates a succession of token embeddings, a BiLSTM network learns the sequential relationships in facial expressions. An all-inclusive representation is created by merging the end forward and backward LSTM's hidden states [39]. By keeping both global context and sequential dependencies, this more feature-rich collection is used to improve classification accuracy [40]. We employ an ensemble method that incorporates BiLSTM and BERT to further improve accuracy. By combining the two architectures' predictions via weighted voting, the ensemble model improves resilience and reduces misclassification [41]. With the sequential learning capability of BiLSTM and the contextual embeddings of BERT, the combination improves emotion recognition performance. Using BERT and BiLSTM, we examine textual data and derive sentiment from contextual assessment for Yelp text-based sentiment analysis. Tokenization, stop-word removal, and stemming are used to preprocess text data. Next, BERT converts the data into embeddings, and figure 3 shows the sequential patterns [43] used to train BiLSTM. An accurate and balanced sentiment categorization [44] is achieved in all scenarios by combining the predictions of both architectures in the ensemble model.

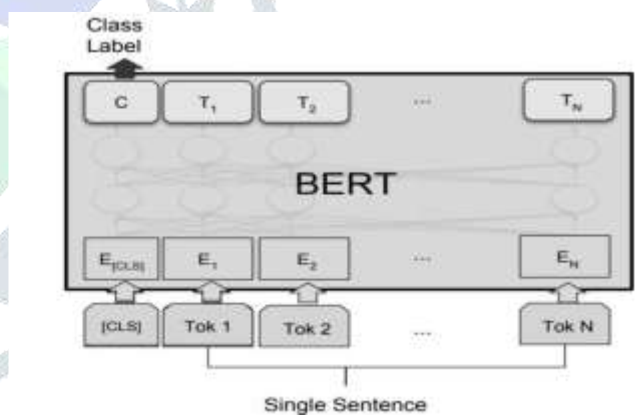

Figure 3: The Framework of Text-Based Emotion Detection using Yelp Dataset

5. Outcome

We test our method on several benchmark datasets. Based on the findings, our BERT-based BiLSTM technique achieves better accuracy and F1-score than the current emotion detection models. Built to handle natural language processing, BERT is one of the latest DL-based models [45]. BERT excels in text categorization tasks because it concurrently gathers information from a word's context and its meaning [46]. One kind of recurrent neural network that can remember textual long-distance associations is the BiLSTM model. It improves the model's contextual awareness by processing sequences in both forward and reverse order [47]. By incorporating BiLSTM layer learning with BERT's contextual embeddings, our ensemble model merges the two methods' best features [48]. This improves the model's ability to detect emotional signals in the

Yelp text dataset [49]. Class probabilities are generated for every test sample by the model. In this study, we evaluate the suggested BERT-based BiLSTM model against state-of-the-art methods. You can see the outcomes of the assessment in Table 1. These results demonstrate that our proposed technique is more effective than existing methods in emotion detection tests [50].

Table 1. The Model Performance Metrics

Model	Precision	Recall	F1-score	Accuracy
BILSTM	0.76	0.79	0.77	0.79
BERT+BILSTM	0.68	0.82	0.72	0.85
BERT	0.73	0.77	0.47	0.77

Figure 4 highlights the usefulness of sequential learning paired with transformer-based embeddings for modelling contextual dependencies. The BiLSTM model achieved an 85% score on the Yelp Dataset (Text-based Emotion Detection).

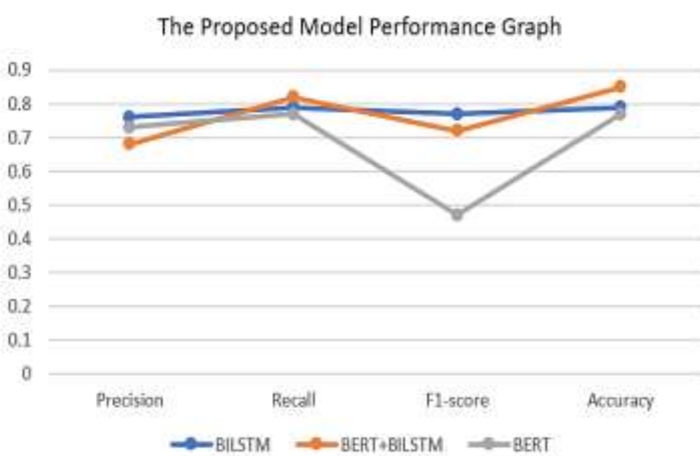

Figure 4: The Proposed Model Performance Graph

6. Barriers in Sentiment and Emotion Analysis

A significant amount of data is being produced by individuals in the form of informal writing in this age of the Internet. As seen in figure 5, social networking sites bring a variety of issues, some of which include typographical errors, the introduction of new terminology, and the inappropriate application of grammar. As a result of these obstacles, it is difficult for robots to do analysis of mood and emotion. There are instances when people are unable to articulate their feelings in a straightforward manner. "Y have you been sooo late?" is an example of a statement in which the word "why" is misspelled as "y," the word "you" is misspelled as "u," and the word "soooo" is used to emphasize the importance of the sentence [51]. In addition, this statement does not indicate if the individual is anxious or upset over the situation. Therefore, the identification of mood and emotion from data collected from the actual world is fraught with difficulties for a number of different reasons. An insufficient amount of resources is one of the difficulties encountered throughout the process of emotion identification and sentiment analysis. A huge dataset that has been annotated is necessary for some statistical procedures, for instance. The collection of data, on the other hand, is not a difficult task; nevertheless, the manual labelling of a huge dataset is a time-consuming process that is also less reliable [52]. One additional issue that arises with respect to resources is the fact that the majority of these materials are only accessible in the English language. Therefore, sentiment analysis and emotion identification from languages other than English, particularly regional languages, provide academics with a significant problem as well as an opportunity. Additionally, some of the lexicons and corpora are reserved for a particular domain, which restricts their ability to be used in other domains.

Figure 5: The Barriers in Sentiment and Emotion Analysis

7. Conclusion

The term "sentiment analysis" refers to a technique that is used to determine the attitudes, feelings, and emotions that individuals have in relation to a certain objective, which may include individuals, activities, organizations, services, topics, and goods. Rather than just reporting if something is favourable, bad, or neutral, emotion detection is a subset of sentiment analysis since it makes predictions about the specific emotion being expressed. Recent years have seen a significant increase in the number of researchers working on speech and facial expressions for the purpose of emotion identification. The identification of emotions in written text, on the other hand, is a laborious job since, unlike in spoken language, there are no indicators present, such as tonal stress, facial expression, pitch, and so on. Using natural language processing (NLP) techniques, numerous ways have been presented in the past for the purpose of identifying emotions from text. These methods include the keyword approach, the lexicon-based approach, and the machine learning approach. In spite of this, there were certain limitations associated with techniques that were focused on keywords and lexicons since they concentrate on semantic linkages. Using BERT-based feature extraction and BiLSTM approaches, we developed a robust approach to emotion identification in text in this study. The strategy used both of these techniques. By integrating deep contextual embeddings with sequential learning, our model is able to efficiently capture subtle emotional signals, in contrast to traditional techniques, which are prone to being weak against contextual ambiguity and poor generalization. In contrast to the Multi-Label Emotion Detection Architecture presented in the base work, which makes use of a multi-channel emotion specified feature extractor and an emotion correlation learner, our technique is cantered on the use of pre-trained BERT embeddings in conjunction with BiLSTM for sequential learning. Our ensemble model, which is comprised of BERT and BiLSTM, attained an accuracy of 85%, which indicates that it is able to identify more subtle emotional signals in text data.

8. Future Work

In the years to come, we will explore other classifiers and ensemble methods to enhance the outcomes. Furthermore, we shall focus on the composition of textual sentences and some regional languages. Furthermore, in the digital realm, individuals' engagement in sending text messages, posting tweets, and composing online product evaluations has significantly increased and is in high demand. Consequently, possessing extensive data enables the development of a real-time, text-based emotion identification model to identify individuals' feelings or moods.

References

[1] Nyalalani Smarts, Rajalakshmi Selvaraj, Venumadhav Kuthadi, "Natural Language Processing Revolution From Humble Beginnings to Deep Learning and Beyond", 2024 IEEE 4th International Conference on ICT in Business Industry & Government (ICTBIG), pp.1-13, 2024

[2] Y. Perwej, Firoj Parwej, “A Neuroplasticity (Brain Plasticity) Approach to Use in Artificial Neural Network”, International Journal of Scientific & Engineering Research (IJSER), France, ISSN 2229 – 5518, Volume 3, Issue 6, Pages 1- 9, June 2012, DOI: 10.13140/2.1.1693.2808

[3] Y. Perwej, “The Bidirectional Long-Short-Term Memory Neural Network based Word Retrieval for Arabic Documents”, Transactions on Machine Learning and Artificial Intelligence (TMLAI), Society for Science and Education, United Kingdom (UK), ISSN 2054-7390, Volume 3, Issue 1, Pages 16 - 27, Feb 2015, DOI: 10.14738/tmlai.31.863

[4] Y. Perwej, “Unsupervised Feature Learning for Text Pattern Analysis with Emotional Data Collection: A Novel System for Big Data Analytics”, IEEE International Conference on Advanced computing Technologies & Applications (ICACTA'22), SCOPUS, IEEE No: #54488 ISBN No Xplore: 978-1-6654-9515-8, Coimbatore, India, 4-5 March 2022, DOI: 10.1109/ICACTA54488.2022.9753501

[5] Batbaatar E, Li M, Ryu KH (2019) Semantic-emotion neural network for emotion recognition from text. IEEE Access 7:111866–111878

[6] Neha Kulshrestha, Nikhat Akhtar, Y. Perwej, “Deep Learning Models for Object Recognition and Quality Surveillance”, Accepted International Conference on Emerging Trends in IoT and Computing Technologies (ICEICT-2022), ISBN 978-10324-852-49, SCOPUS, Routledge, Taylor & Francis, CRC Press, Chapter 75, pages 508-518, Goel Institute of Technology & Management, Lucknow, May 2022, Link - https://www.routledge.com/Emerging-Trends-in-IoT-and-Computing-Technologies-Proceedings-of-International/Tripathi-Verma/p/book/9781032485249#, DOI: 10.1201/9781003350057-75

[7] Kumar Bibhuti B. Singh, Nikhat Akhtar, Devendra Agarwal, Susheel Kumar, Y. Perwej, “An Evaluation of OpenCV's Investigation into Hand Gesture Recognition Methods”, International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN: 2395-1990, Online ISSN: 2394-4099, Volume 12, Issue 1, Pages 01-14, January 2025, DOI: 10.32628/IJSRSET25121150

[8] Neha Anand, Arpita Vishwakarma, Yusuf Perwej, Neeta Bhusal Sharma, Atifa Parveen, “A Hybrid Deep Learning Ensemble Approach for Enhanced Data Mining Efficiency”, Journal of Emerging Technologies and Innovative Research (JETIR), ISSN-2349-5162, Volume 12, Issue 8, Pages 268 - 276, August 2025, DOI: 10.6084/m9.jetir.JETIR2508238

[9] Soleymani, M., Asghari-Esfeden, S., Pantic, M., & Fu, Y. (2014). Continuous emotion detection using EEG signals and facial expressions. In 2014 IEEE international conference on multimedia and expo (ICME) (pp. 1-6).

[10] Albornoz, E. M., Milone, D. H. & Rufiner, H. L. (2017). Feature extraction based on bio-inspired model for robust emotion recognition. Soft Computing, 21(17), 5145-5158

[11] Y. Perwej, “An Evaluation of Deep Learning Miniature Concerning in Soft Computing”, International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE), ISSN (Online): 2278-1021, ISSN (Print): 2319-5940, Volume 4, Issue 2, Pages 10 - 16, 2015, DOI: 10.17148/IJARCCE.2015.4203

[12] Y. Perwej, “Recurrent Neural Network Method in Arabic Words Recognition System”, International Journal of Computer Science and Telecommunications (IJCST), Sysbase Solution (Ltd), UK, London, (http://www.ijcst.org) , ISSN 2047-3338, Volume 3, Issue 11, Pages 43-48, 2012

[13] A. A. Alnuaim, M. Zakariah, P. K. Shukla et al., “Human computer interaction for recognizing speech emotions using multilayer perceptron classiAer,” Journal of Healthcare Engineering, vol. 2022, Article ID 6005446, 12 pages, 2022.

[14] Shubham Mishra, Mrs Versha Verma, Nikhat Akhtar, Shivam Chaturvedi, Y. Perwej, “An Intelligent Motion Detection Using OpenCV” , International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN: 2395-1990 , Online ISSN : 2394-4099, Volume 9, Issue 2, Pages 51-63, 2022, DOI: 10.32628/IJSRSET22925

[15] Kajal, Neha Singh, Nikhat Akhtar, Ms. Sana Rabbani, Yusuf Perwej, Susheel Kumar, “Using Emerging Deep Convolutional Neural Networks (DCNN) Learning Techniques for Detecting Phony News”, International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN: 2456-3307, Volume 10, Issue 1, Pages 122-137, 2024, DOI: 10.32628/CSEIT2410113

[16] A. S. Rajawat, P. Bedi, S. B. Goyal et al., “Fog big data analysis for IoT sensor application using fusion deep learning,” Mathematical Problems in Engineering, vol. 2021, Article ID 6876688, 16 pages, 2021.

[17] Kajal, Neha Singh, Nikhat Akhtar, Ms. Sana Rabbani, Yusuf Perwej, Susheel Kumar, “Using Emerging Deep Convolutional Neural Networks (DCNN) Learning Techniques for Detecting Phony News”, International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN: 2456-3307, Volume 10, Issue 1, Pages 122-137, 2024, DOI: 10.32628/CSEIT2410113

[18] A. Rodriguez, Y. L. Chen, and C. Argueta, “FADOHS: framework for detection and integration of unstructured data of hate speech on facebook using sentiment and emotion analysis,” IEEE Access, vol. 10, pp. 22400–22419, 2022.

[19] Firoj Parwej, Nikhat Akhtar, Yusuf Perwej, “A Close-Up View About Spark in Big Data Jurisdiction”, International Journal of Engineering Research and Application (IJERA), ISSN: 2248-9622, Volume 8, Issue 1, (Part -I1), Pages 26-41, January 2018, DOI: 10.9790/9622-0801022641

[20] L. Cao, S. Peng, P. Yin, Y. Zhou, A. Yang, and X. Li, “A survey of emotion analysis in text based on deep learning,” in Proceedings of the 2020 IEEE 8th International Conference on

Smart City and Informatization (iSCI), pp. 81–88, IEEE, Guangzhou, China, December 2020.
[21] Dileep Kumar Gupta, Prof. (Dr.) Devendra Agarwal, Y. Perwej, Opinder Vishwakarma, Priya Mishra, Nitya, "Sensing Human Emotion using Emerging Machine Learning Techniques", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN: 2395-1990, Online ISSN: 2394-4099, Volume 11, Issue 4, Pages 80-91, 2024, DOI: 10.32628/IJSRSET24114104
[22] Onyenwe I, Nwagbo S, Mbeledogu N, Onyedinma E (2020) The impact of political party/candidate on the election results from a sentiment analysis perspective using# anambradecides2017 tweets. Soc Netw Anal Min 10(1):1–17
[23] Y. Perwej, Nikhat Akhtar, Devendra Agarwal, "The emerging technologies of Artificial Intelligence of Things (AIoT) current scenario, challenges, and opportunities", Book Title "Convergence of Artificial Intelligence and Internet of Things for Industrial Automation", SCOPUS, ISBN: 978-1-032-42844-4, CRC Press, Taylor & Francis Group, 2024 Link: https://www.taylorfrancis.com/chapters/edit/10.1201/9781003509240-1/emerging-technologiesartificial-intelligence-things-aiot-current-scenario-challenges-opportunities-yusuf-perwej-nikhatakhtar-devendra-agarwal?context=ubx&refId=537f1a8f-6a94-4439-b337-3ad3d1ce8845, DOI: 10.1201/9781003509240-1
[24] Ma X, Zeng J, Peng L, Fortino G, Zhang Y (2019) Modeling multiaspects within one opinionated sentence simultaneously for aspect-level sentiment analysis. Future Gener Comput Syst 93:304–311
[25] Y. Perwej, "A Smart Framework for Detecting Instagram Fake Accounts using Machine Learning and Correlation & Singular Value Decomposition Techniques," J. Emerging Technologies and Inno. Research, vol. 10, no. 9, pp. b772, 2023
[26] Prabowo R, Thelwall M (2009) Sentiment analysis: a combined approach. J Inform 3(2):143–157
[27] Apoorva Dwivedi, Basant Ballabh Dumka, Nikhat Akhtar, Ms Farah Shan, Yusuf Perwej, "Tropical Convolutional Neural Networks (TCNNs) Based Methods for Breast Cancer Diagnosis", International Journal of Scientific Research in Science and Technology (IJSRST), Print ISSN: 2395-6011, Online ISSN: 2395-602X, Volume 10, Issue 3, Pages 1100 - 1116, May-June- 2023, DOI: 10.32628/IJSRST523103183
[28] Albornoz, E. M., Milone, D. H. & Rufiner, H. L. (2017). Feature extraction based on bio-inspired model for robust emotion recognition. Soft Computing, 21(17), 5145-5158
[29] Asghar and Nabiha, "Yelp Dataset Challenge: Review Rating Prediction," arXiv.org, 17 - May - 2016.
[30] Y. Perwej, "Unsupervised Feature Learning for Text Pattern Analysis with Emotional Data Collection: A Novel System for Big Data Analytics", IEEE International Conference on Advanced computing Technologies & Applications (ICACTA'22), SCOPUS, IEEE No: #54488 ISBN No Xplore: 978-1-6654-9515-8, Coimbatore, India, 4-5 March 2022, DOI: 10.1109/ICACTA54488.2022.9753501
[31] Y. Perwej, "Performance Analysis for Cloud Based OLAP over Big Data", IEEE International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES -2022), SCOPUS, IEEE Conference, St. Joseph's Institute of Technology, IEEE Electronic ISBN:978-1-6654-7413-9, Chennai, India, 15th &16th July 2022, DOI: 10.1109/ICSES55317.2022.9914266
[32] J. X. Chen, D. M. Jiang, and Y. N. Zhang, "A hierarchical bidirectional GRU model with attention for EEG-based emotion classi Acation," IEEE Access, vol. 7, pp. 118530–118540, 2019
[33] Nikhat Akhtar, Kumar Bibhuti B. Singh, Devendra Agarwal, Y. Perwej, "Improving Quality of Life with Emerging AI and IoT Based Healthcare Monitoring Systems", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN: 2456-3307, Volume 11, Issue 1, Pages 96-107, January 2025, DOI: 10.32628/CSEIT2514551
[34] Mahmoud AbouGhaly, Y. Perwej, Mumdouh Mirghani Mohamed Hassan, Nikhat Akhtar, "Smart Sensors and Intelligent Systems: Applications in Engineering Monitoring", International Journal of Intelligent Systems and Applications in Engineering, SCOPUS, ISSN: 2147- 6799, Volume 12, Issue 22s, Pages 720–727, July 2024
[35] Y. Perwej, "Recurrent Neural Network Method in Arabic Words Recognition System", International Journal of Computer Science and Telecommunications (IJCST), which is published by Sysbase Solution (Ltd), UK, London, (http://www.ijcst.org) , ISSN 2047-3338, Volume 3, Issue 11, Pages 43-48, 2012
[36] F. M. Alotaibi, "Classifying text-based emotions using logistic regression," VAWKUM Transactions on Computer Sciences, vol. 7, no. 1, pp. 31–37, 2019
[37] D. Pan and J. Nie, "Mutux at semeval-2018 task 1: Exploring Impacts of Context Information on Emotion Detection", in Proc.12th Int. Workshop Semantic Eval., 2018, pp. 345–349.
[38] Shamim Ahmad, Farheen Siddiqui, Dr. Yusuf Perwej, Homa Rizvi, Dr. Nikhat Akhtar, "Modelling Crop Yield with Deep CNN-LSTM for Spatiotemporal Data Analysis", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN: 2456-3307, Volume 11, Issue 5, Pages 54-64, September 2025, DOI: 10.32628/CSEIT25111697
[39] Mahmoud AbouGhaly, Y. Perwej, Mumdouh Mirghani Mohamed Hassan, Nikhat Akhtar, "Smart Sensors and Intelligent Systems: Applications in Engineering Monitoring", International Journal of Intelligent Systems and Applications in Engineering, SCOPUS, ISSN: 2147- 6799, Volume 12, Issue 22s, Pages 720–727, July 2024
[40] N. Colneric and J. Demsar, "Emotion recognition on twitter: Com- parative study and training a unison model," IEEE Trans. Affective Comput., vol. 11, no. 3, pp. 433–446, Third Quarter 2018.
[41] A. Rodriguez, Y. L. Chen, and C. Argueta, "FADOHS: framework for detection and integration of unstructured data of hate speech on facebook using sentiment and emotion analysis," IEEE Access, vol. 10, pp. 22400–22419, 2022
[42] Sarvesh Kumar, Y. Perwej, Farheen Siddiqui, Ankit Shukla, Dr. Nikhat Akhtar, "A Data-Driven Framework for Fake News Detection Via Web Scraping and Machine Learning Approach", International Journal of Innovative Science and Research Technology (IJISRT), ISSN- 2456-2165, Volume 10, Issue 6, Pages 1391 - 1404, June 2025, DOI: 10.38124/ijisrt/25jun1003
[43] P. Xu, A. Madotto, C. S. Wu, J. H. Park, and P. Fung, "Emo2vec: learning generalized emotion representation by multi-task training," 2018
[44] Farheen Siddiqui, Sana Rabbani, Y. Perwej, Hina Rabbani, Dr. Nikhat Akhtar, "Leveraging Cloud Computing, IoT and Big Data for Intelligent Infrastructure Management in Smart Cities", Journal of Emerging Technologies and Innovative Research (JETIR), ISSN-2349-5162, Volume 12, Issue 8, Pages 301 - 310, August 2025, DOI: 10.6084/m9.jetir.JETIR2508335
[45] Nagarjuna Tandra, Nikhat Akhtar, K Padmanaban, L. Guganathan, "A finite-element dual-level contextual informed

neural network with swarm space hopping algorithm based optimal feature selection and detection for EEG-based epileptic seizure detection", Swarm and Evolutionary Computation, Elsevier , SCIE, Volume 97, Pages 1- 19, August 2025, DOI: 10.1016/j.swevo.2025.102072

[46] D. Ghazi, D. Inkpen, and S. Szpakowicz, "Detecting emotion stimuli in emotion-bearing sentences," Computational Linguistics and Intelligent Text Processing, Springer, Cham, pp. 152–165, 2015

[47] Farheen Siddiqui, Homa Rizvi, Y. Perwej, Shamim Ahmad, Dr. Nikhat Akhtar, "Leveraging AI for Social Impact in Environmental Sustainability", Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN: 2395-1990, Online ISSN: 2394-4099, Volume 12, No. 4, Pages 253-266, August 2025, DOI: 10.32628/IJSRSET2512506

[48] C. R. Chopade, "Text based emotion recognition: a survey," International Journal of Science and Research, vol. 2, no. 6, pp. 409–414, 2015

[49] Nourah Alswaidan and Mohamed El Bachir Menai. 2020. A survey of state-of-the-art approaches for emotion recognition in text Knowledge Info. Systems 62, 8 (2020), 2937–2987

[50] Iqra Ameer, Grigori Sidorov, Helena Gomez-Adorno, and Rao Muhammad Adeel Nawab. 2022. Multi-label emotion classification in code-mixed text: Data and methods. IEEE Access 10 (2022), 8779–8789

[51] Batbaatar E, Li M, Ryu KH (2019) Semantic-emotion neural network for emotion recognition from text. IEEE Access 7:111866–111878

[52] Balahur A, Turchi M (2014) Comparative experiments using supervised learning and machine translation for multilingual sentiment analysis. Computer Speech Lang 28(1):56–75