Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 1, February 2025, pp. 551~559
ISSN: 2302-9285, DOI: 10.11591/eei.v14i1.7617

Hybrid deep learning: a comparative study on ai algorithms in natural language processing for text classification

Md. Mahmudul Hasan, Rajesh Kumar Das, Mocksidul Hassan, Sultana Razia, Jannatul Ferdous Ani, Sharun Akter Khushbu, Mirajul Islam
Department of Computer Science and Engineering, Faculty of Science and Information Technology, Daffodil International University, Dhaka, Bangladesh

Article Info

Article history:

Received Sep 27, 2023
Revised Sep 2, 2024
Accepted Sep 28, 2024

Keywords:

Classification
E-commerce
Hybrid deep learning
Machine learning
Natural language processing

ABSTRACT

The objective of this research project is to assess the effectiveness of various machine learning algorithms, including deep learning and combination approaches, in performing tasks such as categorizing products into specific categories using data from an e-commerce platform named "OTHOBA." In this study, a dataset consisting of 19,087 data samples is used to evaluate the effectiveness of seven supervised machine learning models. Among these models are three based on deep learning: long short-term memory (LSTM), bidirectional long short-term memory (Bi-LSTM), and 1D convolutional (Conv1D), as well as a multi-layer model that combines Conv1D and LSTM approaches. The task at hand is the classification of product categories. The LSTM-based model demonstrates the highest accuracy rate of 96.23% among the deep learning models, while the logistic regression (LR) models achieve the highest accuracy scores of 97.00% for product category classification. Overall, the proposed models and techniques show significant progress in natural language processing (NLP) research for text classification, specifically in English, and have practical applications for e-commerce sites.

Corresponding Author:

Mirajul Islam
Department of Computer Science and Engineering, Faculty of Science and Information Technology
Daffodil International University
Dhaka 1341, Bangladesh
Email: merajul15-9627@diu.edu.bd

1. INTRODUCTION

The remarkable progress in natural language processing (NLP) and the ability of machines to effectively analyze and categorize large volumes of textual data demonstrate their capabilities in classification tasks. NLP is concerned with comprehending and interpreting human language. As big data and machine learning continue to grow, these fields have become increasingly vital. English is the most common language for scientific publications, making it a focal point for NLP applications in scientific research and knowledge extraction [1]-[3]. The focus on English in NLP is driven by its wide usage and accessibility of resources, which makes it an ideal language for NLP research and development [4], [5]. Text classification is a common task in the field of NLP that involves assigning labels or categories to various types of textual data, such as documents, paragraphs, sentences, or queries. This task is discussed in multiple sources [6]-[8]. Since digital documents were first introduced, automatic text classification has been a significant area of both research and practical application [9], [10]. Text classification has become increasingly significant due to its numerous applications in different fields, including but not limited to sentiment analysis, spam detection, message classification, user intent classification, and topic modeling [11], [12]. It helps to automatically organize and categorize large amounts of text data, making it more manageable and understandable. NLP is utilized in text classification as it empowers computers to comprehend a handle human language. It improves the precision of text classification, and handles the complexity of natural language, sparsity, and high-dimensionality of text data [13]. In NLP, several methods are used to perform sentiment analysis or text classification tasks, including rule-based systems, probabilistic classifiers, supervised learning models, non-parametric methods, tree-based models, deep learning models, and ensemble methods. Rule-based systems use a set of predefined rules to classify text, such as keywords or regular expressions [14], [15]. The Naïve Bayes classifier that employs Bayes theorem in a probabilistic manner that is known for being simple, efficient, and straightforward to implement, as referenced in source [16]. Conversely, support vector machines (SVM) can adeptly categorize data in spaces with numerous dimensions and are also beneficial for classification tasks that are non-linear [17]. The k-nearest neighbors (KNN) technique is a type of non-parametric approach that utilizes the proximity of documents in the training set to classify text [18]. Decision trees (DT), random forests (RF) are tree-based models that create a DT and RF to classify text [19], [20]. Neural networks are deep learning models that can use various architectures such as long short-term memory (LSTM), recurrent neural network (RNN), convolutional neural network (CNN), and bidirectional long short-term memory (Bi-LSTM) to classify text. Ensemble techniques are employed to enhance the classifier's performance by combining the predictions of several models. The amalgamation of predictions from multiple models helps improve the overall accuracy and robustness of the classifier. An extensively used type of RNN for processing sequential data in NLP applications is LSTM [21]. One of the advantages of using LSTM in text classification is its ability to capture long-term dependencies and retain information for a significant period. LSTMs are versatile and can be utilized for various text classification tasks, including sentiment analysis to identify the polarity of a text as positive, negative, or neutral, detecting spam messages, generating text similar to a given input, recognizing named entities such as people and businesses mentioned in a text, and creating a summary of a longer text by extracting the most important information. As opposed to, CNNs have gained popularity not only for image and video processing tasks but also for their potential use in classifying text data [22]. The application of machine learning models has become increasingly popular in various fields in recent years, including sentiment analysis, price prediction, and time series analysis. This literature review examines several recent research articles that propose various approaches to these areas. In one study, in reference to source [23], the researchers suggested utilizing a CNN along with an embedding layer and LSTM to classify emotions and sentiment in YouTube comments.

In this study, we employed seven supervised classification models: multinomial Naïve Bayes (MNB), SVM, KNN, DT, RF, logistic regression (LR), and stochastic gradient descent (SGD). Furthermore, we utilized three distinct deep learning models-LSTM, Bi-LSTM, and 1D-convolutional (Conv1D) neural network in addition to a hybrid multi-layer model combining Conv1D and LSTM for the classification of product categories. The key contributions of this paper can be summarized as follows: i) the dataset constructed in this study, consisting of 19087 data samples, can serve as a valuable resource for future research in product category classification and ii) a diverse set of supervised classification models and deep learning models were employed in this study, including MNB, SVM, KNN, DT, RF, LR, SGD, LSTM, Bi-LSTM, Conv1D, and a hybrid Conv1D and LSTM model, to accurately classify product categories.

The paper follows the following structure: the paper is structured into three major sections. Section 2 details the research method and materials used in the study. Section 3 includes the experimental analysis, encompassing the performance and outcomes of the various machine learning models applied in the study. Lastly, section 4, which addresses conclusion and scope for future research.

2. METHOD

In this section, we will explain the techniques and methodologies that we employed in our work of text classification. The working flow in Figure 1 depicts the overall process of the study, providing a visual representation of the various stages involved in the process.

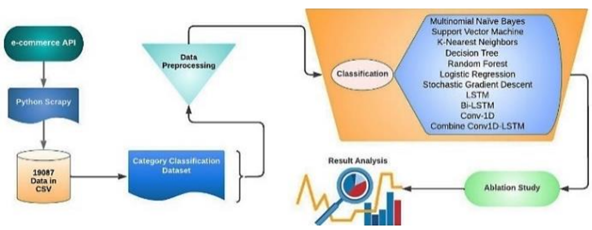


Figure 1. Working flow of the entire process

2.1. Dataset properties

The study utilized data from Othoba.com, a Bengali e-commerce platform, collected with Python Scrappy. The dataset included date, category, product name, brand, seller, price, shipping price, city, ratings, outlet size, and total. This research formed the basis for a text classification task, where "product name" was used as the feature column, and "category" as the target column. The study employed a dataset consisting of 19,087 samples, classified into nine categories, and applied various classification methods as shown in Figure 2.

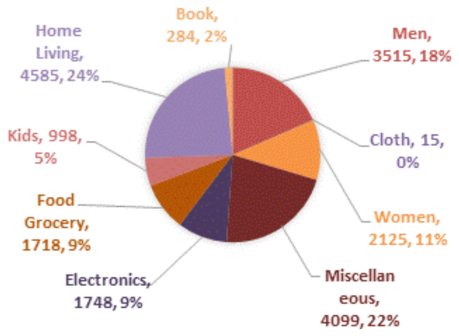


Figure 2. Dataset overview for text classification

2.2. Dataset preprocessing

The preprocessing steps taken to prepare the dataset for classification involved several techniques to transform and normalize the text data. The following is a brief description of the preprocessing methods used in this study:

- Data cleaning: we enhanced data quality for classification by removing stop words, punctuation, and null values. This streamlined the dataset, reducing noise and boosting classification precision. Stop word removal minimized irrelevant content, eliminating punctuation, special characters, remove emoji, remove small, and large text. Organizing data into categories further improved dataset integrity.
- Tokenization: tokenization, a critical step in text classification, involves converting text into tokens (words or phrases). Our study employed techniques such as stemming to simplify and enhance accuracy. Lowercasing standardized text but requires caution regarding potential loss of information like proper nouns and acronyms. Task-specific decisions govern lowercasing usage.
- Normalization: text normalization standardizes text and enhances ML performance in classification by reducing features while preserving vital information. Techniques like lemmatization and stemming ensure text consistency, aiding effective dimensionality reduction.
- Vectorization: for effective text processing by machine learning, conversion to numerical form is essential. Vectorization achieves this, a key step in text classification. We utilized bag-of-words: text represented as word counts. Example: "The quick brown fox..." becomes [1, 1, 1, 1, 1, 1, 1, 1], each integer showing word frequency.
- Splitting into training and testing sets: splitting text data into training and testing sets is crucial for model evaluation. non-overlapping samples ensure unbiased assessments. Standard metrics like accuracy, precision, recall, and F1 score are employed for evaluation.
- Balancing the data: balancing data in text classification ensures equal samples per class, crucial due to common imbalances. For instance, sentiment analysis datasets might have more positives than negatives. Imbalance can lead to biased learning, favoring majority class and undermining minority class predictions.

2.3. Supervised machine learning models

After data preparation, machine learning models employ processed info for training and prediction. Data splits into 80:20 for training and testing, 15,269 and 3,818 samples respectively. Model learns on training data, minimizing error via parameter adjustments. Trained model predicts unseen data, assessed using metrics like accuracy, precision, recall, and F1 score, indicating predictive prowess.

2.4. Deep learning based models

This study develops and deploys four neural network models: LSTM, Bi-LSTM, Conv1D, and Conv1D-LSTM hybrid. Dataset split into training, testing, and validation sets (Figure 3). Model performance assessed using standard metrics: accuracy, precision, recall, and F1 score, widely used in machine learning literature for evaluation.

- LSTM: deep neural network architecture, excels in processing sequential data like text, speech, and time series. Comprising LSTM cells with memory capabilities, it can capture long-term dependencies, making it ideal for tasks such as speech recognition and language modeling, as shown in Figure 4(a) of our specialized LSTM model.
- BiLSTM: is a RNN that employs two LSTM models. Unlike standard LSTMs, it processes sequences both forward and backward, considering past and future context. This makes it ideal for tasks like NLP, speech recognition, and image captioning. Bi-LSTM models excel in sequence modeling, and Figure 4(b) showcases their architecture.
- CNN: notably used in computer vision, process data through interconnected layers, applying convolution operations. These layers capture intricate input features by sliding filters across data. Non-linear activation functions, like ReLU, introduce non-linearity. Figure 4(c) illustrates our proposed CNN model.
- Hybrid Conv1D-LSTM: combining CNNs and LSTMs enhances performance in tasks like speech recognition and NLP. Conv1D layers find local patterns, while LSTM layers capture long-term dependencies. The Hybrid Conv1D-LSTM model excels in analyzing sequential data with both local and global features. Figure 4(d) depicts our proposed Hybrid Conv1D-LSTM model.

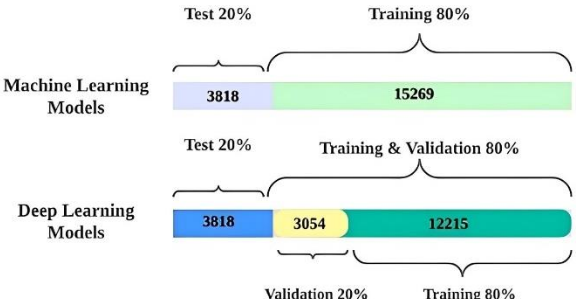
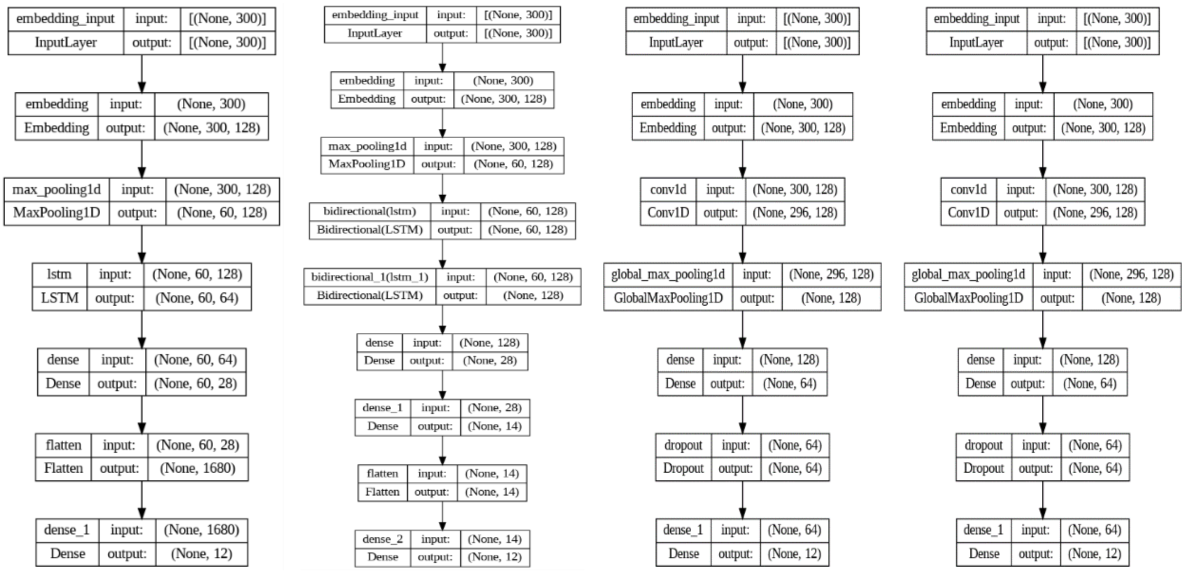


Figure 3. Dataset splitting



(a) (b) (c) (d)

Figure 4. Architectures of proposed models; (a) LSTM, (b), Bi-LSTM (c), CNN, and (d) hybrid Conv1D-LSTM

2.5. Experimental setup

The study involved testing diverse deep learning algorithms through four classifiers. Python 3.8, Keras, TensorFlow 2.4.1, and Pandas facilitated experimentation, preprocessing, and visualization. Scikit-learn computed performance metrics. Models were compiled with Adam optimizer and 'sparse_categorical_crossentropy' loss. Each model underwent 50 epochs with consistent batch size 64.

3. RESULTS AND DISCUSSION

The evaluation of seven classification models in Table 1, including MNB, SVM, KNN, DT, RF, LR, and SGD, showcased varying performance metrics. LR led with a 97.00% accuracy, while MNB scored the lowest at 92.69%. Notably, DT, RF, and SGD achieved perfect precision scores, contrasting with MNB lowest recall score. In contrast, for text data classification, a study in Table 2 explored four models: LSTM-based, Bi-LSTM-based, Conv1D-based, and Conv1D-LSTM-based. The LSTM-based model demonstrated superior accuracy at 96.23%, surpassing conventional LR. LSTM's capability to capture intricate temporal relationships within text data distinguishes it from LR, showcasing the power of deep learning for complex data. Model choice should align with data characteristics and analysis objectives.

Table 1. Performance of the ML algorithms for product category classification

Model name	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
MNB	92.69	93.47	92.69	92.60
SVM	96.00	98.00	96.00	96.00
KNN	93.00	99.00	93.00	94.00
DT	93.00	100	93.00	94.00
RF	96.00	100	96.00	96.00
LR	97.00	98.00	97.00	97.00
SGD	96.00	100	96.00	96.00

Table 2. Performance of the deep learning algorithms for product category classification

Model	Category	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
LSTM	Men	90.77	92.19	91.47	96.23
	Cloth	15.38	40.00	22.22	
	Women	95.82	98.66	97.22	
	Miscellaneous	94.99	94.99	94.99	
	Electronics	94.54	92.51	93.51	
	Food grocery	97.72	94.84	96.26	
	Kids	97.32	97.10	97.21	
	Home living	96.79	98.22	97.50	
	Book	96.67	95.31	95.98	
Bi-LSTM	Men	95.92	73.44	83.19	95.76
	Cloth	66.67	80.00	72.73	
	Women	98.31	94.09	96.15	
	Miscellaneous	94.75	95.54	95.15	
	Electronics	80.37	94.12	86.70	
	Food grocery	94.29	97.30	95.77	
	Kids	97.01	97.77	97.39	
	Home living	99.39	96.74	98.05	
	Book	95.86	95.07	95.46	
Conv1D	Men	82.43	95.31	88.41	95.13
	Cloth	50.00	60.00	54.55	
	Women	97.30	97.04	97.17	
	Miscellaneous	94.32	97.21	95.75	
	Electronics	92.63	94.12	93.37	
	Food grocery	97.29	97.05	97.17	
	Kids	97.32	97.10	97.21	
	Home living	98.22	98.22	98.22	
	Book	97.35	94.95	96.14	
Combine	Men	81.94	92.19	86.76	96.20
Conv1D-LSTM	Cloth	25.00	20.00	22.22	
	Women	96.32	98.39	97.34	
	Miscellaneous	92.23	95.82	93.99	
	Electronics	89.05	95.72	92.27	
	Food grocery	96.52	95.33	95.92	
	Kids	97.64	96.77	97.20	
	Home living	98.52	98.52	98.52	
	Book	97.69	94.25	95.94	

In Figures 5(a) to (d), the accuracy trends of various neural network models across training and validation datasets are illustrated with respect to the number of training epochs. The results indicate that accuracy generally improves until a saturation point is reached, beyond which further epochs yield marginal gains. This improvement rate varies across models and languages, highlighting model-specific nuances. Figures 6(a) to (d) portrays the loss dynamics of four neural network models across training and validation datasets concerning epoch count. Loss typically diminishes with increasing epochs until a plateau, signifying diminishing returns. Additionally, the elevated validation dataset loss compared to the training dataset hints at potential overfitting. These findings underscore the importance of judiciously selecting the number of epochs and vigilantly monitoring loss across both datasets to prevent overfitting and optimize model performance. The presented Table 3 highlights a comprehensive comparison of sentiment analysis studies, each employing distinct datasets and methodologies. In comparison, our study stands out with an impressive 97.00% accuracy using LR on a dataset of 19,087 raw entries, showcasing its superior performance in sentiment classification.

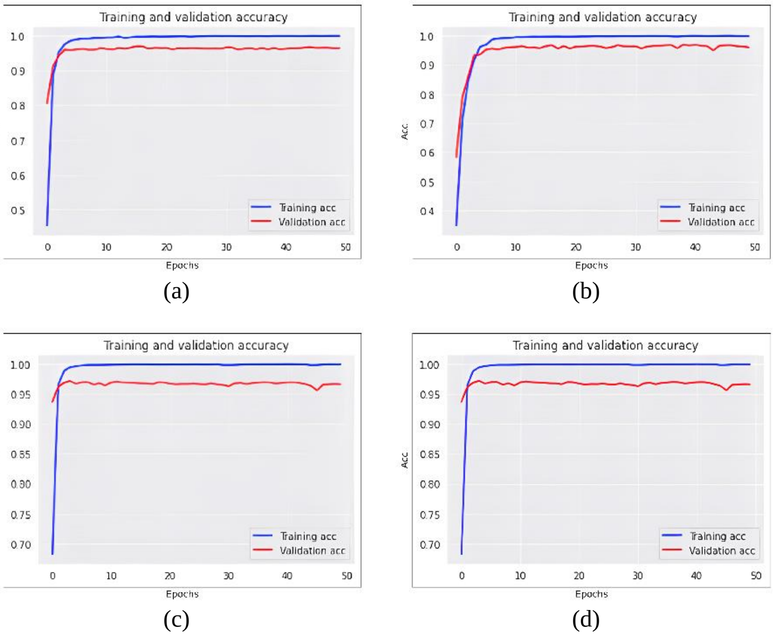


Figure 5. Relationship between each deep learning models training and validation accuracy; (a) effectiveness of LSTM, (b) effectiveness of Bi- LSTM, (c) effectiveness of Conv1D, and (d) effectiveness of Conv1D-LSTM

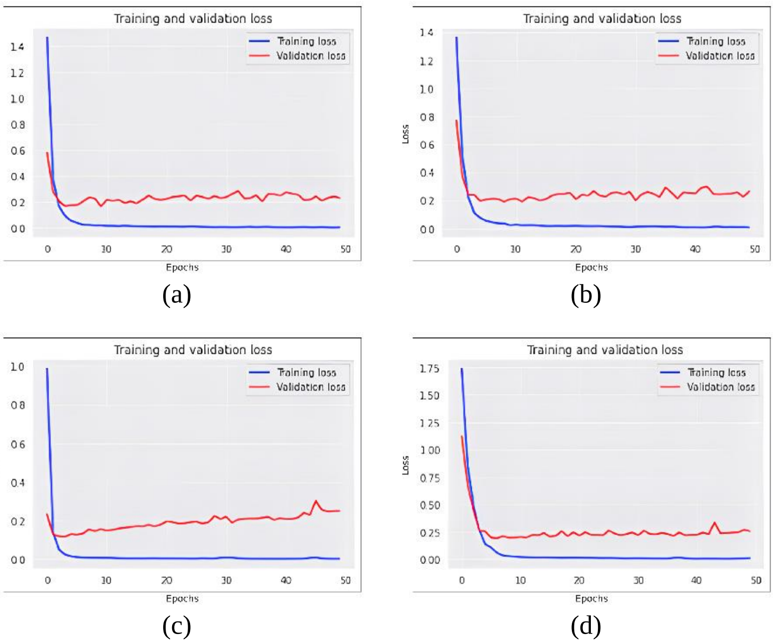


Figure 6. Plot showing the relationship between each deep learning models training and validation loss; (a) effectiveness of LSTM, (b) effectiveness of Bi- LSTM, (c) effectiveness of Conv1D, and (d) effectiveness of Conv1D-LSTM

Table 3. Comparison with others state of art studies

Paper	Dataset	Method and techniques	Results (%)
Das *et al.* [24]	2,577 reviews both Bangla and English	Stemming algorithm: porter SVM	English Acc 82.56 Bangla Acc 86.43
Islam *et al.* [25]	4545 blogs	Unigram TF-IDF SVM	Acc 87.4
Hamid *et al.* [26]	8,110 slang words	LR	Acc 70
Daud *et al.* [27]	40,063 English news articles	Optimized SVM	Acc 85
Alsaidi *et al.* [28]	568 English poems	Roughest theory algorithm	Acc 85
This study	19,087 raw data	LR	Acc 97.00

4. CONCLUSION

This research advances the field of NLP for text classification, specifically focusing on product categorization within the e-commerce domain. The diverse set of supervised classification models and deep learning approaches examined, such as LSTM, Bi-LSTM, and hybrid Conv1D-LSTM, underscores the breadth of methodologies available for tackling this complex task. The achieved 96.23% accuracy by the LSTM-based model and 97.00% by LR demonstrate the effectiveness of these models in product category classification. The construction of a substantial dataset comprising 19,087 samples stands as a valuable contribution, offering a resource for future research in this domain. The practical implications are profound, with implications for enhancing e-commerce platforms like "OTHOBA" through improved product categorization, leading to a more efficient and user-friendly shopping experience. These findings bridge the theoretical and practical realms, providing insights and tools that can be harnessed for advancements in NLP applications, particularly within the realm of e-commerce. Future research should extend to multilingual contexts, explore adaptability to diverse e-commerce domains, fine-tune hyperparameters for efficiency, transition models to real-time scenarios, and integrate user feedback. Embracing linguistic diversity, addressing platform-specific constraints, and refining model dynamics offer promising directions for advancing the broader field of text classification in e-commerce.

REFERENCES

[1] C. Dreisbach, T. A. Koleck, P. E. Bourne, and S. Bakken, "A systematic review of natural language processing and text mining of symptoms from electronic patient-authored text data," *International Journal of Medical Informatics*, vol. 125, pp. 37–46, 2019, doi: 10.1016/j.ijmedinf.2019.02.008.

[2] R. Ferreira-Mello, M. André, A. Pinheiro, E. Costa, and C. Romero, "Text mining in education," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 9, no. 6, 2019, doi: 10.1002/widm.1332.

[3] S. Minaee, N. Kalchbrenner, E. Cambria, N. Nikzad, M. Chenaghlu, and J. Gao, "Deep learning--based text classification: a comprehensive review," *ACM computing surveys (CSUR)*, vol. 54, no. 3, pp. 1–40, 2021.

[4] D. Khurana, A. Koli, K. Khatter, and S. Singh, "Natural language processing: state of the art, current trends and challenges," *Multimedia Tools and Applications*, vol. 82, no. 3, pp. 3713–3744, 2023, doi: 10.1007/s11042-022-13428-4.

[5] K. Olga, H. Tanjin, H. Haoyan, T. Amalie, Elsa A. Olivetti, and C. Gerbrand, "Opportunities and challenges of text mining in materials research," *iScience*, vol. 24, no. 3, 2021, doi: 10.1016/j.isci.2021.10215

[6] K. Kowsari, K. J. Meimandi, M. Heidarysafa, S. Mendu, L. Barnes, and D. Brown, "Text classification algorithms: a survey," *Information (Switzerland)*, vol. 10, no. 4, pp. 1-68, 2019, doi: 10.3390/info10040150.

[7] A. Guha, D. Samanta, A. Banerjee, and D. Agarwal, "A deep learning model for information loss prevention from multi-page digital documents," *IEEE Access*, vol. 9, pp. 80451–80465, 2021, doi: 10.1109/ACCESS.2021.3084841.

[8] X. Chen, H. Xie, G. Cheng, L. K. M. Poon, M. Leng, and F. L. Wang, "Trends and features of the applications of natural language processing techniques for clinical trials text analysis," *Applied Sciences (Switzerland)*, vol. 10, no. 6, pp. 1-36, 2020, doi: 10.3390/app10062157.

[9] F. Amato, G. Cozzolino, V. Moscato, and F. Moscato, "Analyse digital forensic evidences through a semantic-based methodology and NLP techniques," *Future Generation Computer Systems*, vol. 98, pp. 297–307, 2019, doi: 10.1016/j.future.2019.02.040.

[10] W. Fang, H. Luo, S. Xu, P. E. D. Love, Z. Lu, and C. Ye, "Automated text classification of near-misses from safety reports: an improved deep learning approach," *Advanced Engineering Informatics*, vol. 44, 2020, doi: 10.1016/j.aei.2020.101060.

[11] Z. Alom, B. Carminati, and E. Ferrari, "A deep learning model for Twitter spam detection," *Online Social Networks and Media*, vol. 18, 2020, doi: 10.1016/j.osnem.2020.100079.

[12] S. Larson *et al.*, "An evaluation dataset for intent classification and out-of-scope prediction," *EMNLP-IJCNLP 2019 - 2019 Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing, Proceedings of the Conference*, pp. 1906–1912, 2021.

[13] G. Liu and J. Guo, "Bidirectional LSTM with attention mechanism and convolutional layer for text classification," *Neurocomputing*, vol. 337, pp. 325–338, 2019, doi: 10.1016/j.neucom.2019.01.078.

[14] W. H. Bangyal *et al.*, "Detection of fake news text classification on COVID-19 using deep learning approaches," *Computational and Mathematical Methods in Medicine*, pp. 1–14, 2021, doi: 10.1155/2021/5514220.

[15] M. Topaz *et al.*, "Mining fall-related information in clinical notes: comparison of rule-based and novel word embedding-based machine learning approaches," *Journal of Biomedical Informatics*, vol. 90, 2019, doi: 10.1016/j.jbi.2019.103103.

[16] J. Jefriyanto, N. Ainun, and M. A. Ardha, "Application of Naïve Bayes classification to analyze performance using stopwords," *Journal of Information System, Technology and Engineering*, vol. 1, no. 2, pp. 49–53, 2023. doi: 10.61487/jiste.v1i2.15.

[17] J. S. Raj and J. V. Ananthi, "Recurrent neural networks and nonlinear prediction in support vector machines," *Journal of Soft Computing Paradigm*, vol. 1, no. 1, pp. 33–40, 2019, doi: 10.36548/jscp.2019.1.004.

[18] J. C. Lerian and G. Chenayan, "The implementation of multi-label k-nearest neighbor algorithm to classify essay answers," *Journal of Information System, Technology and Engineering*, vol. 1, no. 3, pp. 89–94, 2023. doi: 10.61487/jiste.v1i3.38.

[19] M. Bansal, A. Goyal, and A. Choudhary, "A comparative analysis of K-Nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning," *Decision Analytics Journal*, vol. 3, 2022, doi: 10.1016/j.dajour.2022.100071.
[20] S. Kanish, P. Henil, S. Devanshi, and S. Manan, "A comparative analysis of logistic regression, random forest and KNN models for the text classification," *Augmented Human Research*, vol. 5, no. 12, pp. 1–16, 2020.
[21] J. C. W. Lin, Y. Shao, Y. Djenouri, and U. Yun, "ASRNN: a recurrent neural network with an attention model for sequence labeling," *Knowledge-Based Systems*, vol. 212, 2021, doi: 10.1016/j.knosys.2020.106548.
[22] G. Convolutional and T. Classification, "Graph convolutional networks for text classification," in *Proceedings of the AAAI conference on artificial intelligence*, 2019, pp. 7370–7377.
[23] N. Irtiza Trinto and M. Eunus Ali, "Detecting multilabel sentiment and emotions from Bangla YouTube comments," in *2018 International Conference on Bangla Speech and Language Processing, ICBSLP 2018*, IEEE, Sep. 2018, pp. 1–6. doi: 10.1109/ICBSLP.2018.8554875.
[24] R. K. Das, M. Islam, M. M. Hasan, S. Razia, M. Hassan, and S. A. Khushbu, "Sentiment analysis in multilingual context: comparative analysis of machine learning and hybrid deep learning models," *Heliyon*, vol. 9, no. 9, 2023, doi: 10.1016/j.heliyon.2023.e20281.
[25] T. Islam, A. I. Prince, M. M. Z. Khan, M. I. Jabiullah, and M. T. Habib, "An in-depth exploration of bangla blog post classification," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 2, pp. 742–749, 2021, doi: 10.11591/eei.v10i2.2873.
[26] M. A. Hamid, E. S. Tumpa, J. A. Polin, J. Al Nahian, A. Rahman, and N. A. Mim, "Bengali Slang detection using state-of-the-art supervised models from a given text," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 4, pp. 2381–2387, 2023, doi: 10.11591/beei.v12i4.4743.
[27] S. Daud, M. Ullah, A. Rehman, T. Saba, R. Damaševičius, and A. Sattar, "Topic classification of online news articles using optimized machine learning models," *Computers*, vol. 12, no. 1, pp. 164–221, 2023, doi: 10.3390/computers12010016.
[28] S. A. Alsaidi, A. T. Sadiq, and H. S. Abdullah, "English poems categorization using text mining and rough set theory," *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 4, pp. 1701–1710, 2020, doi: 10.11591/eei.v9i4.1898.

BIOGRAPHIES OF AUTHORS

Md. Mahmudul Hasan is a recent graduate with a B.Sc. in computer science and engineering from Daffodil International University, Bangladesh. He has a strong foundation in programming, data structures, research, and web development. With a keen interest in research, Mahmudul actively contributes to various sectors, particularly in NLP, machine learning, and deep learning. For further communication or collaborative opportunities. He can be contacted at email: mahmudul15-13284@diu.edu.bd.

Rajesh Kumar Das received his bachelor's degree in computer science and engineering from Daffodil International University, Bangladesh. Presently, he serves as an Instructor at Daffodil International Professional Training Institute, specializing in Python and Django courses. His ongoing research focuses on data science, natural language processing, machine learning, deep learning, with a specific emphasis on their application to the Bangla language. He can be contacted at email: rajesh15-13032@diu.edu.bd.

Mocksidul Hassan is a B.Sc. student in computer science and engineering at Daffodil International University, stands out for his prowess in research and leadership. Actively involved in university clubs, his true passion lies in pushing the boundaries of technology through focused research contributions. Beyond academia, he dedicates his technical skills to community service initiatives, embodying a vision that merges academic excellence with meaningful societal impact. He is the epitome of a student who seamlessly integrates research, leadership, and social responsibility in his journey. He can be contacted at email: mocksidul15-13881@diu.edu.bd.

Sultana Razia is a student at the Daffodil International University in Bangladesh studying computer science and engineering, being interested in research, networking, and extracurricular activities. She is interested in machine learning, data science, image processing, NLP, and deep learning. She is currently working on different areas of research. She can be contacted at email: sultana15-14285@diu.edu.bd.

Jannatul Ferdous Ani completed her bachelor's degree in computer science and engineering from Daffodil International University, Bangladesh. She is currently working as an IT Officer at a renowned bank in Bangladesh. Her research interests include machine learning, deep learning, image processing, natural language processing, computer vision, pattern recognition, data mining, and human-computer interaction (HCI). She can be contacted at email: jannatul15-10483@diu.edu.bd.

Sharun Akter Khushbu is currently employed as a Lecturer (Senior Scale) in computer science and engineering at Daffodil International University. She received a bachelor of science in computer science and engineering (CSE) from Daffodil as well as a master's program. During the master's research and development project, she was employed as a research assistant on a research project. This research project work was carried out in collaboration with the International Company Apurba-DIU Research and Development Lab, Bangladesh. Previously, she worked as a research assistant for Apurba Technologies Ltd., a USA-based software firm specializing in providing machine learning solutions for expertise. After four months in that role, she moved back into academia. Her current research interests lie in computer vision and natural language processing, machine learning, and deep learning. She can be contacted at email: sharun.cse@diu.edu.bd.

Mirajul Islam a computer science and engineering graduate from Daffodil International University, Dhaka, Bangladesh, is a dedicated researcher with a profound impact on academia. Specializing in machine learning, deep learning, cybersecurity, natural language processing, image processing, computer vision, and more, his 10+ Scopus-indexed journals and 10+ Scopus-indexed conference publications attest to his significant contributions. His research spans diverse technological domains, showcasing a commitment to pushing the boundaries of knowledge. His work not only enriches academic discourse but also holds practical implications, contributing to advancements in technology. He is trajectory as a thought leader and innovator positions him as a beacon in the dynamic realm of research and data science, inspiring others to explore the intersections of technology and drive meaningful change. He can be contacted at email: merajul15-9627@diu.edu.bd.