TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 23, No. 2, April 2025, pp. 329~339
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v23i2.26110

Detecting fake news through deep learning: a current systematic review

Idza Aisara Norabid, Masita Jalil, Rozniza Ali, Noor Hafhizah Abd Rahim
Artificial Intelligence Research Interest Group, Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, Kuala Terengganu, Malaysia

Article Info

Article history:

Received Feb 25, 2024
Revised Nov 28, 2024
Accepted Dec 26, 2024

Keywords:

Deep learning
Machine learning
Misinformation detection
Natural language processing
Systematic review

ABSTRACT

This systematic review explores the domain of deep learning-based fake new detection employing advanced search practices on Scopus and Web of Science (WoS) databases with keywords “fake news,” “deep learning,” and “method.” The study encompasses 33 articles categorized into three main themes: i) dataset and benchmarking for fake news detection, ii) multimodal approaches for fake news detection, and iii) deep learning applications and techniques for fake news detection. The analysis reveals the significance of curated datasets and robust benchmarking in improving the efficacy of fake news detection models. Additionally, the review highlights the emergence of multimodal approaches that integrate textual and visual information for improved detection accuracy. The findings clarify the essential role of deep learning applications, emphasizing the development of sophisticated models for automated identification of fake news. This systematic study adds to a thorough grasp of current research trends and offers insightful information for future developments in the field of deep learning-based false news identification.

Corresponding Author:

Noor Hafhizah Abd Rahim
Artificial Intelligence Research Interest Group, Faculty of Computer Science and Mathematics
Universiti Malaysia Terengganu
21030 Kuala Nerus, Terengganu, Malaysia
Email: noorhafhizah@umt.edu.my

1. INTRODUCTION

In an era dominated by digital information and unparalleled connectivity, the widespread misinformation presents a serious threat to the core of societal conversation [1], [2]. The deliberate spread of misleading content, often driven by malicious intentions, erodes the foundations of an informed public. Given the seriousness of the problem, it is becoming more and more important to establish robust mechanisms for detecting and combating fake news. This article aims to investigate an innovative approach to this challenge by exploring deep learning, a branch of artificial intelligence (AI) that has proven to be very effective in identifying intricate patterns in large-scale datasets [3], [4].

The rapid evolution of communication technologies, particularly with the rise of social media, has accelerated the spread of information, hence complicating the task to distinguish between truth and deception. Conventional methods of fake news detection, relying on rule-based systems and manual fact-checking, are proving inadequate given the sheer volume and sophistication of misinformation [5]–[7]. Deep learning, harnessing the capabilities of neural networks and advanced algorithms, emerges as a promising solution to address these shortcomings [8]–[10]. By empowering machines to learn and adapt from vast datasets, deep learning models can uncover subtle patterns and complex details associated with fake news, thereby enhancing our capacity to identify and counter deceptive narratives [11].

Previous studies have shown that deep learning techniques can be effective in detecting fake news. For instance, a study [12] has investigated the practicality of utilising deep learning to differentiate false information on the internet just based on textual content. The study demonstrated the practicality of deep learning approaches in tackling the serious problem of fake news in modern society. It presented three unique neural network structures with one of them utilising bidirectional encoder representations from transformers (BERT). Furthermore, Sastrawan *et al.* [13] demonstrated the effectiveness convolutional neural network-recurrent neural networks (CNN-RNN) fusion-based methods in detecting fake news, highlighting the capability of deep learning-based approaches for achieving more precise in the detection of fake news, surpassing the performance of conventional machine learning techniques.

In addition, Hamed *et al.* [14] presented an approach utilizing a bidirectional long short-term memory (LSTM) model, a form of neural network architecture. This work emphasized the challenging nature of automated fake news detection and the significance of creating models that are capable of understanding the relatedness of reported news. Moreover, Kausar *et al.* [15] seeks to overcome the constraints of current fake news detection methods by introducing a hybrid model that integrates N-gram and TF-IDF for content-based feature extraction. Additionally, it employs advanced deep learning models like LSTM or BERT for sequential feature extraction. The proposed model has exceptional performance, achieving impressive precision.

Furthermore, Verma *et al.* [16] introduces the message credibility (MCred) framework, which combines both BERT and CNN with N-gram features, for global text semantics and local text semantics, respectively. This framework exhibited improved precision in comparison to the advanced models currently accessible. MCred emphasizes the importance of integrating both local and global text semantics to achieve more efficient detection of fake news. Expanding the horizon of fake news detection, Nadeem *et al.* [17] propose a hybrid HyproBert model that integrates DistilBERT, CNN, and bidirectional gated recurrent units (BiGRU). Their work showcases the model's higher performance when compared to both conventional methods and contemporary approaches, indicating the potential of hybrid approaches.

Overall, this recent research highlights the the constantly evolving nature of fake news detection, emphasising the ongoing need for efficient and adaptive deep learning models to address the dynamic problems given by the rapid growth of misinformation strategies. These studies also highlight the need of tackling the issues associated with automated fake news detection, as well as the need for more advanced models capable of determining the relatedness of reported news. Thus, this article attempts to offer an in-depth review of the landscape of fake news detection through the lens of deep learning. It will examine the underlying theoretical principles that support these models, exploring how neural networks can independently verify the authenticity of information. Additionally, the practical implications of implementing deep learning in real-world scenarios will be examined, including challenges and the potential impact on the broader information ecosystem. This paper intends to contribute to the ongoing discussion on strengthening information channels against the pervasive threat of false news by navigating the intersection of technology, information science and societal resilience.

The rest of the paper is structured as follows. In section 2, the methods used to systematically select eligible articles for analysis are described. The results of the analysis of all the chosen articles and their discussion are presented in section 3. Lastly, a conclusion is provided in section 4.

2. METHOD

2.1. Identification

For this study, an extensive body of relevant literature was selected through the application of key stages within the systematic review methodology. Following the identification of keywords, related terms were systematically identified and refined using dictionaries, thesauri, encyclopedias, and an analysis of prior research. The selection of all relevant keywords was made following the creation of search strings for Scopus and WoS as in Table 1. A compilation of 716 papers was obtained from the two databases in the initiation of the systematic review process. For manuscript publication, all provided figures must follow the standard of quality for publication.

Table 1. The query string

Indexing database	Search string
Scopus	TITLE-ABS-KEY ("Fake News" AND (detect*) AND "Deep Learning" AND method)
WoS	"Fake News" AND (detect*) AND "Deep Learning" AND method

2.2. Screening

The first stage of screening involved a thorough examination of a collection of possibly relevant research materials to determine content that is in line with the predefined research question(s). During this phase, an orderly elimination procedure was implemented to eliminate any duplicate papers from the initially obtained list of papers. 609 publications were excluded during the initial screening step. Afterwards, a total of 107 papers were subjected to further examination in the subsequent phase, during which specific exclusion and inclusion criteria, as outlined in Table 2 of this study, were implemented. The main criterion utilized in this approach was literature (research papers), as it constitutes the principal source of practical recommendations. This includes various types of academic publications such as research papers, books, book series, chapters, reviews, meta-synthesis, meta-analyses, and conference proceedings. These publications were not considered in the previous study. It is important to mention that the review was limited to literature written in English. Importantly, the strategy solely concentrated on articles specifically from the year 2023. As a result, 38 papers were rejected due to repetitive criteria.

Table 2. The query string

Criterion	Inclusion	Exclusion
Language	English	Non-english
Timeline	2023	<2023
Document type	Journal (article)	Conference, book, review
Publication stage	Final	In press

2.3. Eligibility

A comprehensive collection of 69 articles was compiled in the third stage, denoted as eligibility assessment. During this phase, a comprehensive analysis was performed on the titles and primary content of each article to ensure that the inclusion criteria is met and in line with the objectives of the current research. Thus, 36 reports were ruled out due to incongruence with the study's objectives, as indicated by insufficient relevance in the titles and abstracts, as well as a lack of full-text accessibility. Ultimately, 33 articles meet the eligibility criteria and are available for further review.

2.4. Data abstraction and analysis

An evaluative methodology employed in this research involved an integrative analysis that comprehensively examined and synthesized diverse research designs, particularly those employing quantitative approaches. The primary aim of this proficient study was identifying the appropriate subjects and subtopics in the development of themes involved in the acquisition of data. Figure 1 illustrates the method by which a selection of 33 articles were carefully examined in search of claims or information pertinent to the subjects under investigation.

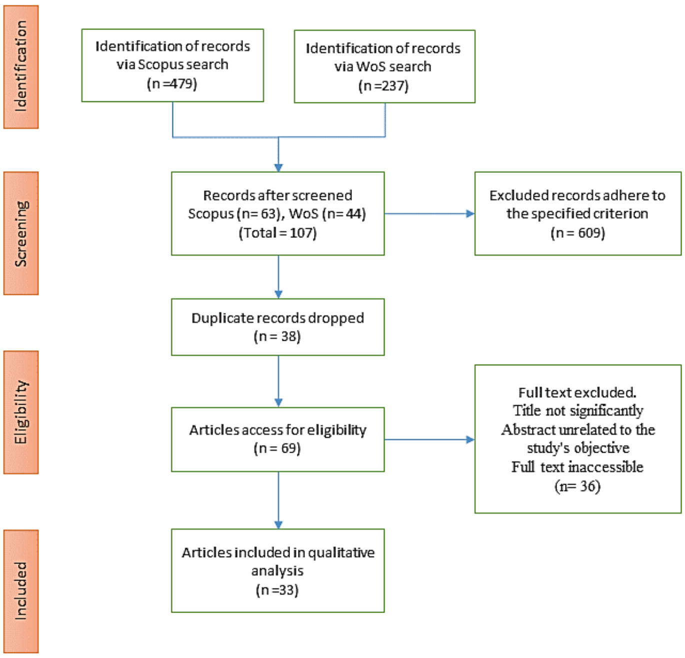

Figure 1. Flow diagram of the proposed searching study [18]

The authors then reviewed the important recent research on deep learning-based false news identification. A comprehensive review of the study results and methodologies employed in all prior investigations is currently underway. Subsequently, collaboration among co-authors facilitated the development of thematic constructs grounded in the contextual framework of the study's data. During the data analysis process, a detailed journal was meticulously maintained to document relevant observations, perspectives, challenges, and other critical concepts essential for accurate data interpretation. The evaluation of potential inconsistencies in the thematic design process was subsequently undertaken by comparing outcomes. It is imperative to highlight that any disparities in opinions regarding the aforementioned concepts were subject to thorough debate among the authors. Ultimately, the themes generated underwent refinement to ensure internal coherence. To validate the challenges encountered, two experts—specialized in text analytics and deep learning respectively conducted the analytical selection process. The phase of expert assessment serves to ensure that each subtheme is clear, significant, and appropriate through the establishment of domain validity.

3. RESULTS AND DISCUSSION

Within the context of information sharing, the rise of fake news poses a significant threat, influencing public opinion and society interactions. Efforts to counter this challenge involve the development of advanced detection models. These models are trained with benchmark datasets containing a wide variety of fake news samples, are capable of to learn and adapt to different patterns and characteristics indicative of falsified information. For instance, Keya *et al.* [19] introduced FakeStack, a fake news detection model that are trained on multiple datasets, the model demonstrated impressive accuracy, outperforming baseline models in detecting fake news acros s various datasets. Research by Merryton and Augasta [20] introduce AA-BiLSTM framework as in Figure 2.

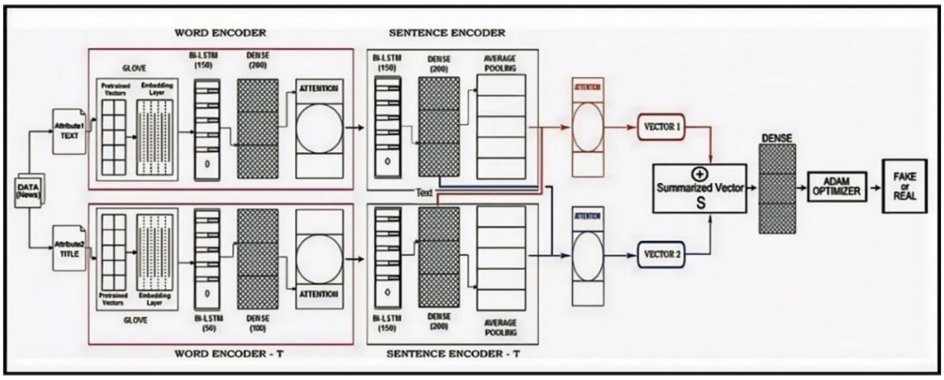

Figure 2. AA-BiLSTM framework introduced by Merryton and Augasta [20]

The model is trained and evaluated on benchmark datasets specifically ISOT, Liar, Kaggle fake real news (2016) and (2022). The model proposed by Hamza *et al.* [21], trained on a fake news dataset, utilizes a quad channel long short-term memory (LSTM) architecture and achieves impressive accuracy in classifying fake news. Ahmad *et al.* [22] proposed a robust benchmark for detecting propagandist text using the RoBERTa model, achieving high accuracy rates on the ProText library, effectively contributing to the identification of propaganda in textual data. Rao *et al.* [23] tackle social spam on platforms merging three datasets; fake news, SMS spam and ling spam for training and evaluation which resulted in the efficacy of the proposed framework. Another dataset, GossipCop and PolitiFact, were utilized to evaluate the accuracy scores, as highlighted by Jamshidi *et al.* [24]. Dua *et al.* [25] introduced I-FLASH, interpretable fake news detector using LIME and SHAP, that explains its predictions delivering robust accuracies on the FactCheck and FactCheck2 dataset. The model is designed to not only detect fake news but also provide interpretability, enhancing trust in its decisions. A model GraSHE, gated recursive and sequential deep hierarchical encoding, proposed by Kumar *et al.* [26], trained on ISOT fake news, FNC and NELA-17 datasets, showcasing improved performance over existing models. Han *et al.* [27], who propose the multi-source information and local-global relationship of heterogeneous network model named MSLG, evaluated on Twitter15 and Twitter16 datasets. Additionally, Mohawesh *et al.* [28] have expanded the research efforts to include other languages. A multilingual fake news detection that are trained on TALLIP dataset which comprises of multiple languages. Moreover, Hamed *et al.* [29] specifically concentrate on the Islamic domain, trained on a dataset specific to Islamic content called RIDI. These approaches highlight the evolving of techniques on fake news detection, demonstrating advancements in model architectures and application domains while proving to their consistent effectiveness across multiple datasets. The key datasets and models used in these studies are summarized in Table 3.

Table 3. Overview of dataset and benchmarking for fake news detection

Authors	Title	Year	Journal	Methodology	Results
Keya *et al.* [19]	Fakestack: hierarchical tri-bert-cnn-lstm stacked model for effective fake news detection	2023	PLoS ONE	BERT embeddings with CNN featuring skip convolution block and LSTM Dataset: english fake news obtained from Kaggle, LIAR and WELFake	Accuracy of 99.74%. on Kaggle fake news dataset Accuracy of 75.58% on LIAR dataset Accuracy of 98.25% on WELFake dataset
Merryton and Augasta [20]	An attribute-wise attention model with bilstm for an efficient fake news detection	2023	Multimedia Tools and Applications	Bi-LSTM and attribute-wise attention mechanism based on CNN Dataset: ISOT, LIAR, Kaggle fake real news [2022] and Kaggle fake real news [2016]	Accuracy exceeding 99% for the ISOT and Kaggle fake real news 2016 datasets Accuracy of 60.31% on the LIAR dataset
Hamza *et al.* [21]	Optimal quad channel LSTM based fake news classification on english corpus	2023	Computer Systems Science and Engineering	LSTM-based model Dataset: comprises of 21417 real and 23481 fake news	Accuracy of 99.12%
Ahmad *et al.* [22]	Robust benchmark for propagandist text detection and mining high-quality data	2023	Mathematics	RoBERTa Dataset: ProText library, dedicated to propaganda texts	Accuracy of 90% on ProText Accuracy of 75% on PTC Accuracy of 68% on TSHP-17 Accuracy of 65% on Qprop
Rao *et al.* [23]	Hybrid ensemble framework with self-attention mechanism for social spam detection on imbalanced data	2023	Expert Systems with Applications	Conv1D and Bi-directional RNN layers with the self-attention mechanism Dataset: fake news datasets, Ling Spam and SMS Spam	Accuracy of 97.26%
Jamshidi *et al.* [24]	A self-attention mechanism-based model for early detection of fake news	2023	IEEE Transactions on Computational Social Systems	Self-attention mechanism-based encoder Dataset: FakeNewsNet (PolitiFact, GossipCop)	GossipCop and PolitiFact F1 scores exceed the best baseline model by 9% and 6%
Dua *et al.* [25]	I-flash: interpretable fake news detector using lime and shap	2023	Wireless Personal Communications	XAI methods; LIME and SHAP Dataset: FactCheck and FactCheck2	Accuracy of 87.25±2.45% on FactCheck, and 92.91±2.07% on FactCheck2
Kumar e*t al.* [26]	Gated recursive and sequential deep hierarchical encoding for detecting incongruent news articles	2023	IEEE Transactions on Computational Social Systems	BiLSTM (Paragraph level), child-sum Tree LSTM (sentence level) Dataset: ISOT fake news, FNC and NELA-17 dataset	Average accuracy of higher than 90%
Han *et al.* [27]	Jointly multi-source information and local-global relations of heterogeneous network for rumour detection	2023	Frontiers in Physics	Graph convolution network Dataset: Twitter15 and Twitter16	Accuracy 92.0% on Twitter15 dataset and 91.3% on Twitter16 dataset
Mohawesh *et al.* [28]	Multilingual deep learning framework for fake news detection using capsule neural network	2023	Journal of Intelligent Information Systems	Capsule neural network for multilingual fake news detection Dataset: TALLIP, included English, Vietnamese, Swahili, Hindi and Indonesian languages.	The accuracy improves across various language pairs
Hamed *et al.* [29]	Disinformation detection about islamic issues on social media using deep learning techniques	2023	Malaysian Journal of Computer Science	BiLSTM-based model. Dataset: Islamic content (RIDI)	Accuracy of 95.42%
Guo *et al.* [30]	A novel fake news detection model for context of mixed languages through multiscale transformer	2023	IEEE Transactions on Computational Social Systems	Multiscale transformer Dataset: Weibo-hybrid include both Chinese and English words	Accuracy approximately 2%-10% higher than baseline models

Researchers have developed diverse automated fake news detection methods, yet challenges persist due to the evolving presence of multimodal information in the form of text and images in news articles and limited multimodal data. Addressing these issues, a multimodal fusion framework called three-level feature-based matching distance multimodal fusion model (TLFND) was proposed [31]. TLFND effortlessly combines textual (headline and body) and visual data in news articles, leveraging both models, Visual Geometry Group 19 also known as VGG-19 and RoBERTa, robustly optimized BERT. Meel and Vishwakarma [32] respond to the escalating misinformation by introducing a veracity analysis system focusing on both textual and visual attributes. Their framework, utilizing BERT and ALBERT, a lite variation of BERT and Inception-ResNet-v2, achieves remarkable accuracy, notably 97.19% on the all data dataset. Nadeem *et al.* [33] address the rise of fabricated news stories using a stylometric and semantic similarity-oriented model (SSM) incorporating hyperbolic hierarchical attention network (Hype-HAN) and EfficientNetB7. An enhanced multimodal fake news detection model was proposed by Kishore and Kumar [34], utilizing the adaptive water strider algorithm (A-WSA) to optimize feature selection for both text and image data. This model demonstrates its effectiveness in automating fake news classification on social media platforms. Moreover, Nadeem *et al.* [35] combines various data types, including contextual, visual and social data extracted from social media and news articles. Advanced models like bidirectional gated recurrent unit (BiGRU) and capsule neural network (CapsNet) are employed to detect fake news, proposing a comprehensive approach for the identification of false news. Yadav *et al.* [36] proposes efficient transformer based multilevel attention (ETMA), as shown in Figure 3, a framework for multimodal detection of fake news. It consists of two transformer-based encoders: one for textual attention and the other for visual attention. These studies emphasize the essential role of multimodal approaches in achieving effective fake news detection. Leveraging advanced models, fusion techniques, and attention mechanisms to overcome challenges in the changing dynamics of information dissemination, where the focus extends beyond the textual side. Table 4 (in Appendix) [31]-[39] provides a detailed outline of these multimodal frameworks and the methodologies applied.

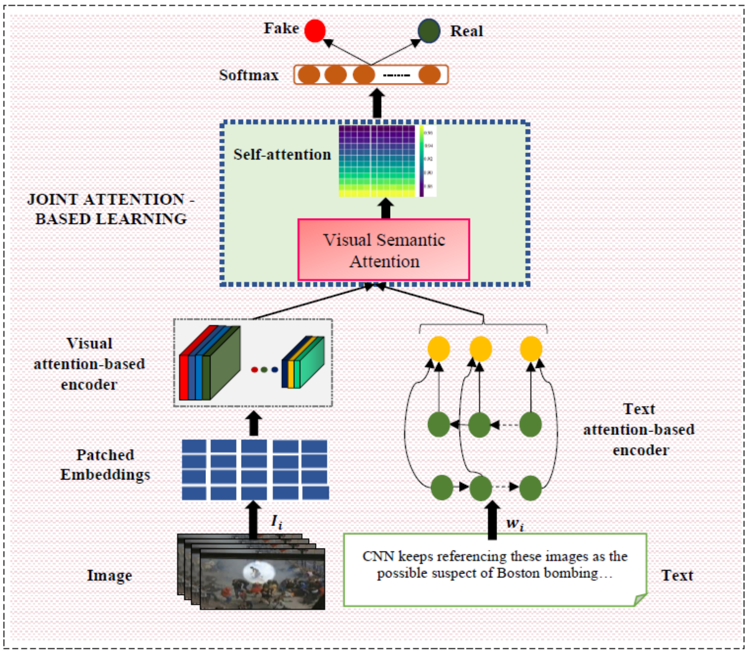

Figure 3. Multimodal ETMA framework by Yadav *et al.* [36]

The increase of inaccurate content on social networking platforms offers a serious threat to public trust in the dynamic world of digital news. In response to this challenge, a range of approaches, notably those deep learning-based models, have been recommended to detect false information. Deep learning, known for its advanced pattern recognition and feature extraction, outperforms traditional machine learning models, enhancing accuracy and reliability in identifying fake news across different datasets and scenarios. One such hybrid-improved deep learning model, presented by Hanshal *et al.* [40] hybridizes convolutional neural network (CNN) with recurrent neural network (RNN), achieving superior performance with 93.87% accuracy. Another approach, introduced by Gao *et al.* [41], employs graph matching and external knowledge to detect fake news utilizing the Bi-GRU-CRF architecture, achieving commendable accuracy rates of 91.07% on a fake news dataset. Devarajan *et al.* [42] proposed an deep-NLP based framework as in Figure 4, and achieved an evaluation performance with average accuracy of 99.72%. Ali *et al.* [43] propose a model called statistical word embedding over linguistic features via deep learning (SWELDL fake), a model integrating statistical word embedding and bidirectional LSTM, achieving an impressive accuracy of 98.52%. Suryawanshi *et al.* [44] present an incremental ensemble neural network that adapts to evolving news patterns, demonstrating consistent performance with 97.90% accuracy. In response to the infodemic during the COVID-19 crisis, Taha *et al.* [45] employ BERT with LSTM model for fake news detection, achieving accuracy rates of higher than 98%. The proposed models by Mallick *et al.* [46] and Wang *et al.* [47] introduce a CNN-based model for fake news refuter identification resulting in high accuracy rates of 98%. These utilizations of deep learning showcase the effectiveness of advanced techniques in combatting the pervasive challenge of misinformation from different angles. As a result, they consistently outperform traditional models with their advanced capabilities. Table 5 (in Appendix) [40], [42]-[51] presents an overview of these deep learning approaches, highlighting the advanced capabilities of the models in addressing misinformation and consistently outperforming traditional methods.

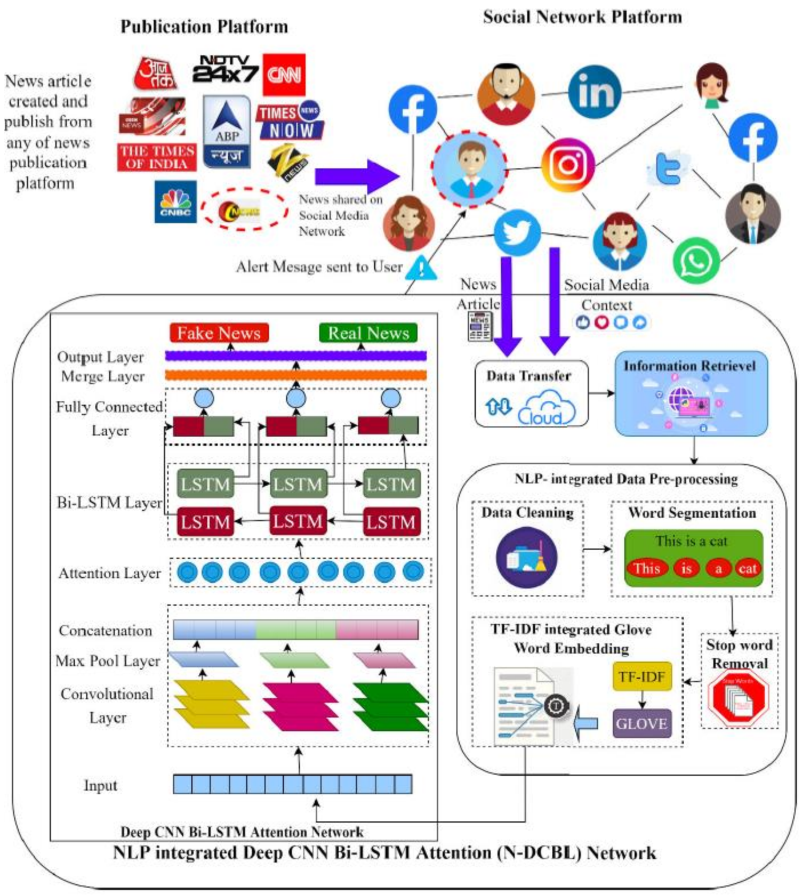

Figure 4. A deep NLP-based framework by Devarajan *et al.* [42]

4. CONCLUSION

This comprehensive analysis offers a thorough analysis of the present state of detecting fake news through the utilisation of deep learning techniques. drawing insights from 33 articles identified through advanced search techniques on Scopus and WoS databases. The review explores three main themes, namely Dataset and Benchmarking for fake news detection, multimodal approaches for fake news detection and deep learning applications and techniques for fake news detection. This exploration highlights the evolving strategies and methodologies in the field. By bringing together these insights, this review enriches the academic discussion on detecting fake news, providing valuable perspectives for researchers and practitioners to guide future initiatives in this crucial domain.

APPENDIX

Table 4. Overview of multimodal approaches for fake news detection

Author	Title	Year	Journal	Methodology	Results
Wang *et al.* [31]	TLFND: a multimodal fusion model based on three-level feature matching distance for fake news detection	2023	Application of Information Theory to Physical Modeling and State Awareness in Complex Systems	Textual: RoBERTa model Visual: VGG-19 model	Accuracy of 94.4% on the PolitiFact dataset and 90.9% on GossipCop dataset
Meel and Vishwakarma [32]	Multi-modal fusion using fine-tuned self-attention and transfer learning for veracity analysis of web information	2023	Social and Information Networks	Textual features: BERT and ALBERT models Visual features: Inception-ResNet-v2	Accuracy of 97.19% on the all data dataset
Nadeem e*t al.* [33]	SSM: stylometric and semantic similarity oriented multimodal fake news detection	2023	Journal of King Saud University - Computer and Information Sciences	Stylometric textual features: Hype-HAN Visual semantic expression: EfficientNetB7 model	Accuracy of higher than 95% on TI-CNN, FNDD and FNSDS dataset
Kishore and Kumar [34]	Enhanced multimodal fake news detection with optimal feature fusion and modified bi-LSTM architecture	2023	Cybernetics and Systems	Image and text features: adaptive water strider algorithm (A-WSA)	Accuracy rate of 96.51%
Nadeem *et al.* [35]	EFND: a semantic, visual, and socially augmented deep framework for extreme fake news detection	2023	Sustainable Education and Social Networks	Contextual data: BiGRU and attention mechanism Visual data: CapsNet with convolution	Accuracy of 0.988% and 0.990% on PolitiFact and GossipCop datasets
Yadav *et al.* [36]	ETMA: efficient transformer-based multilevel attention framework for multimodal fake news detection	2023	IEEE Transactions on Computational Social Systems	Textual features: BERT Visual features: Transformer attention based encoder	Accuracy of above 95% on all four datasets: Jruvika fake news, Pontes fake news, Twitter and Risdal datasets
Al Obaid *et al.* [37]	Robust semi-supervised fake news recognition by effective augmentations and ensemble of diverse deep learners	2023	IEEE Access	Textual features: XLNET transformer Image features: Efficient Net B3	Accuracy of higher than 80% on Gossip, PolitiFact and Juvrika datasets
Sharma *et al.* [38]	Fakedbits- detecting fake information on social platforms using multi-modal features	2023	KSII Transactions on Internet and Information Systems	Textual features: transformer Visual features: EfficientNetB0	Accuracies of 86.48% on MediaEval (Twitter), 82.50% on Weibo, and 88.80% on Fakeddit dataset
Goyal *et al.* [39]	Detection of fake accounts on social media using multimodal data with deep learning	2023	IEEE Transactions on Computational Social Systems	Textual features: LSTM model Visual features: CNN model	Accuracy of 97% on dataset of Twitter accounts

Table 5. Overview of deep learning approaches for fake news detection

Author	Title	Year	Journal	Methodology	Results
Hanshal *et al.* [40]	Hybrid deep learning model for automatic fake news detection	2023	Applied Nanoscience	Hybrid-improved deep learning model; combination of CNN with RNN	Accuracy of 93.87% on Buzzfeed, FakeNewsNet, and FakeNewsChallenges datasets
Devarajan *et al.* [42]	AI-assisted deep NLP-based approach for prediction of fake news from social media users	2023	IEEE Transactions on Computational Social Systems	CNN Bi-LSTM (N-DCBL) attention network	Average accuracy of 99.72% on Buzzface, FakeNewsNet, and Twitter dataset
Ali *et al.* [43]	Linguistic features and bi-LSTM for identification of fake news	2023	Electronics	Bi-LSTM model	Accuracy of 98.52% on SWELDL Fake dataset
Suryawanshi *et al.* [44]	FAKEIDCA: fake news detection with incremental deep learning-based concept drift adaption	2023	Multimedia Tools and Applications	Incremental ensemble neural network	Consistence accuracy of higher than 97% on both Fake and Real news and Getting Real about Fake News datasets

Table 5. Overview of deep learning approaches for fake news detection (*continued*)

Author	Title	Year	Journal	Methodology	Results
Taha *et al.* [45]	Automated COVID-19 misinformation checking system using encoder representation with deep learning models	2023	IAES International Journal of Artificial Intelligence (IJ-AI)	BERT with LSTM mode	Accuracy of 99.1% on COVID-19 dataset
Mallick *et al.* [46]	A cooperative deep learning model for fake news detection in online social networks	2023	Journal of Ambient Intelligence and Humanized Computing	VGG 16, a CNN-based model	Accuracy rate of 98% on data collected from Fake News Detection, ISOT and Fake News datasets
Wang *et al.* [47]	Towards fake news refter identification: mixture of chi-merge grounded cnn approach	2023	Expert Systems with Applications	ERNIE2 model with the Chi-Merge grounded CNN	Accuracy of 85.9%. on nearly 60,000 real-world Sina Weibo data
Jawad and Obaid [48]	The combination of convolution neural networks and deep neural networks for fake news detection	2023	Information Retrieval	Elbow truncated method in combination with CNN and DNN model	Average accuracy of 84.6% on fake news challenge (FNC-1) dataset
Kozik *et al.* [49]	Deep learning for combating misinformation in multicategorical text contents	2023	Deep Learning for Information Fusion and Pattern Recognition	BERT language model	Improvement of nearly 30% in balanced accuracy
Chen *et al.* [50]	Using deep learning models to detect fake news about COVID-19	2023	ACM Transactions on Internet Technology	BiLSTM model	Accuracy of 94%, 99% for short and long sentence of English texts Accuracy at 82% for Chinese texts
Madani *et al.* [51]	Fake news detection using feature extraction, natural language processing, curriculum learning, and deep learning	2023	International Journal of Information Technology & Decision Making	LSTM model	Accuracy of above 95% on fake or real dataset and ISOT dataset Accuracy of above 80% on LIAR and FakeNewsNet dataset

ACKNOWLEDGEMENTS

Financial support for this study was graciously provided by the Fundamental Research Grant Scheme, Ministry of Higher Education Malaysia, designated by grant number FRGS/1/2023/ICT02/UMT/03/1.

REFERENCES

[1] B. C. Neves and J. Borges, "Why does fake news have space on social media? A discussion in the light of infocommunicational behavior and digital marketing," *Informacao e Sociedade*. 2020, doi: 10.22478/ufpb.1809-4783.2020v30n2.50410.

[2] F. Wu and X. Luo, "English Text Recognition Deep Learning Framework to Automatically Identify Fake News," *Computational Intelligence and Neuroscience*, pp. 1–9, 2022, doi: 10.1155/2022/1493493.

[3] A. Mohammed and R. Kora, "An effective ensemble deep learning framework for text classification," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 10, pp. 8825–8837, 2022, doi: 10.1016/j.jksuci.2021.11.001.

[4] S. Habib, M. Alsanea, M. Aloraini, H. S. Al-Rawashdeh, M. Islam, and S. Khan, "An Efficient and Effective Deep Learning-Based Model for Real-Time Face Mask Detection," *Sensors*, vol. 22, no. 7, pp. 1–13, 2022, doi: 10.3390/s22072602.

[5] F. Ghorbanpour, M. Ramezani, M. A. Fazli, and H. R. Rabiee, "FNR: a similarity and transformer-based approach to detect multi-modal fake news in social media," *Social Network Analysis and Mining*, vol. 13, no. 1, p. 56, 2023, doi: 10.1007/s13278-023-01065-0.

[6] M. I. Elias, Y. Mahmud, S. Mutalib, S. N. K. Kamarudin, R. Maskat, and S. A. Rahman, "Fake News Prediction Using Hybrid Model-Systematic Literature Review," in *2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS)*, 2023, pp. 281–286. doi: 10.1109/AiDAS60501.2023.10284628.

[7] S. E. Sorour and H. E. Abdelkader, "Afnd: Arabic Fake News Detection With an Ensemble Deep Cnn-Lstm Model," *Journal of Theoretical and Applied Information Technology*, vol. 100, no. 14, pp. 5072–5086, 2022.

[8] B. Sreedevi, L. P. Narendruni, B. Chitradevi, M. Santhanalakshmi, and G. Sumathi, "A Novel Characterization of the Fake News in Twitter Networks," in *2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, 2023, pp. 825–828. doi: 10.1109/IITCEE57236.2023.10090869.

[9] J. A. Nasir, O. S. Khan, and I. Varlamis, "Fake news detection: A hybrid CNN-RNN based deep learning approach," *International Journal of Information Management Data Insights*, vol. 1, no. 1, pp. 1–13, 2021, doi: 10.1016/j.jjimei.2020.100007.

[10] C. A. C. Sáenz, M. Dias, and K. Becker, "Combining compact news representations generated using DistilBERT and topological features to classify fake news," in *Symposium on Knowledge Discovery, Mining and Learning (KDMiLe)*, 2020, pp. 209–216. doi: 10.5753/kdmile.2020.11978.

[11] T. Chauhan and H. Palivela, "Optimization and improvement of fake news detection using deep learning approaches for societal benefit," *International Journal of Information Management Data Insights*, vol. 1, no. 2, pp. 1–11, 2021, doi: 10.1016/j.jjimei.2021.100051.

[12] Á. I. Rodríguez and L. L. Iglesias, "Fake news detection using deep learning," *arXiv e-prints*, Sep. 2019, doi: 10.48550/arXiv.1910.03496.

[13] I. K. Sastrawan, I. P. A. Bayupati, and D. M. S. Arsa, "Detection of fake news using deep learning CNN–RNN based methods,"

ICT Express, vol. 8, no. 3, pp. 396–408, 2022, doi: 10.1016/j.icte.2021.10.003.
[14] S. K. Hamed, M. J. Ab Aziz, and M. R. Yaakub, "Fake News Detection Model on Social Media by Leveraging Sentiment Analysis of News Content and Emotion Analysis of Users' Comments," *Sensors*, vol. 23, no. 4, pp. 1–26, Feb. 2023, doi: 10.3390/s23041748.
[15] N. Kausar, A. AliKhan, and M. Sattar, "Towards better representation learning using hybrid deep learning model for fake news detection," *Social Network Analysis and Mining*, vol. 12, no. 1, p. 165, Dec. 2022, doi: 10.1007/s13278-022-00986-6.
[16] P. K. Verma, P. Agrawal, V. Madaan, and R. Prodan, "MCred: multi-modal message credibility for fake news detection using BERT and CNN," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 8, pp. 10617–10629, Jul. 2023, doi: 10.1007/s12652-022-04338-2.
[17] M. I. Nadeem *et al.*, "HyproBert: A Fake News Detection Model Based on Deep Hypercontext," *Symmetry*, vol. 15, no. 2, pp. 1–21, Feb. 2023, doi: 10.3390/sym15020296.
[18] D. Moher *et al.*, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *PLoS Medicine*, vol. 6, no. 7, 2009, doi: 10.1371/journal.pmed.1000097.
[19] A. J. Keya, H. H. Shajeeb, M. S. Rahman, and M. F. Mridha, "FakeStack: Hierarchical Tri-BERT-CNN-LSTM stacked model for effective fake news detection," *PLoS One*, vol. 18, no. 12, pp. 1–31, 2023, doi: 10.1371/journal.pone.0294701.
[20] A. R. Merryton and M. G. Augasta, "An Attribute-wise Attention model with BiLSTM for an efficient Fake News Detection," *Multimedia Tools and Applications*, vol. 83, no. 13, pp. 38109–38126, 2024, doi: 10.1007/s11042-023-16824-6.
[21] M. A. Hamza *et al.*, "Optimal Quad Channel Long Short-Term Memory Based Fake News Classification on English Corpus," *Computer Systems Science and Engineering*, vol. 46, no. 3, pp. 3303–3319, 2023, doi: 10.32604/csse.2023.034823.
[22] P. N. Ahmad, Y. Liu, G. Ali, M. A. Wani, and M. ElAffendi, "Robust Benchmark for Propagandist Text Detection and Mining High-Quality Data," *Mathematics*, vol. 11, no. 12, pp. 1–23, Jun. 2023, doi: 10.3390/math11122668.
[23] S. Rao, A. K. Verma, and T. Bhatia, "Hybrid ensemble framework with self-attention mechanism for social spam detection on imbalanced data," *Expert Systems with Applications*, vol. 217, 2023, doi: 10.1016/j.eswa.2023.119594.
[24] B. Jamshidi, S. Hakak, and R. Lu, "A Self-Attention Mechanism-Based Model for Early Detection of Fake News," *IEEE Transactions on Computational Social Systems*, 2023, doi: 10.1109/TCSS.2023.3322160.
[25] V. Dua, A. Rajpal, S. Rajpal, M. Agarwal, and N. Kumar, "I-FLASH: Interpretable Fake News Detector Using LIME and SHAP," *Wireless Personal Communications*, vol. 131, no. 4, pp. 2841–2874, Aug. 2023, doi: 10.1007/s11277-023-10582-2.
[26] S. Kumar, D. Kumar, and S. R. Singh, "Gated Recursive and Sequential Deep Hierarchical Encoding for Detecting Incongruent News Articles," *IEEE Transactions on Computational Social Systems*, vol. 11, no. 1, pp. 1023–1034, 2024, doi: 10.1109/TCSS.2023.3247445.
[27] X. Han, M. Zhao, Y. Zhang, and T. Zhao, "Jointly multi-source information and local-global relations of heterogeneous network for rumor detection," *Frontiers in Physics*, vol. 10, pp. 1–12, 2023, doi: 10.3389/fphy.2022.1056207.
[28] R. Mohawesh, S. Maqsood, and Q. Althebyan, "Multilingual deep learning framework for fake news detection using capsule neural network," *Journal of Intelligent Information Systems*, vol. 60, no. 3, pp. 655–671, 2023, doi: 10.1007/s10844-023-00788-y.
[29] S. K. Hamed, M. J. Ab Aziz, and M. R. Yaakub, "Disinformation Detection About Islamic Issues on Social Media Using Deep Learning Techniques," *Malaysian Journal of Computer Science*, vol. 36, no. 3, pp. 242–270, 2023, doi: 10.22452/mjcs.vol36no3.3.
[30] Z. Guo, Q. Zhang, F. Ding, X. Zhu, and K. Yu, "A Novel Fake News Detection Model for Context of Mixed Languages Through Multiscale Transformer," *IEEE Transactions on Computational Social Systems*, vol. 11, no. 4, pp. 5079–5089, 2024, doi: 10.1109/TCSS.2023.3298480.
[31] J. Wang, J. Zheng, S. Yao, R. Wang, and H. Du, "TLFND: A Multimodal Fusion Model Based on Three-Level Feature Matching Distance for Fake News Detection," *Entropy*, vol. 25, no. 11, pp. 1–17, 2023, doi: 10.3390/e25111533.
[32] P. Meel and D. K. Vishwakarma, "Multi-modal fusion using Fine-tuned Self-attention and transfer learning for veracity analysis of web information," *Expert Systems with Applications*, vol. 229, 2023, doi: 10.1016/j.eswa.2023.120537.
[33] M. I. Nadeem *et al.*, "SSM: Stylometric and semantic similarity oriented multimodal fake news detection," *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 5, pp. 1–17, 2023, doi: 10.1016/j.jksuci.2023.101559.
[34] V. Kishore and M. Kumar, "Enhanced Multimodal Fake News Detection with Optimal Feature Fusion and Modified Bi-LSTM Architecture," *Cybernetics and Systems*, pp. 1–31, 2023, doi: 10.1080/01969722.2023.2175155.
[35] M. I. Nadeem *et al.*, "EFND: A Semantic, Visual, and Socially Augmented Deep Framework for Extreme Fake News Detection," *Sustainability (Switzerland)*, vol. 15, no. 1, pp. 1–24, Jan. 2023, doi: 10.3390/su15010133.
[36] A. Yadav, S. Gaba, H. Khan, I. Budhiraja, A. Singh, and K. K. Singh, "ETMA: Efficient Transformer-Based Multilevel Attention Framework for Multimodal Fake News Detection," *IEEE Transactions on Computational Social Systems*, vol. 11, no. 4, pp. 5015–5027, 2024, doi: 10.1109/TCSS.2023.3255242.
[37] A. Al Obaid, H. Khotanlou, M. Mansoorizadeh, and D. Zabihzadeh, "Robust Semi-Supervised Fake News Recognition by Effective Augmentations and Ensemble of Diverse Deep Learners," *IEEE Access*, vol. 11, pp. 54526–54543, 2023, doi: 10.1109/ACCESS.2023.3278323.
[38] D. K. Sharma, B. Singh, S. Agarwal, H. Kim, and R. Sharma, "FakedBits- Detecting Fake Information on Social Platforms using Multi-Modal Features," *KSII Transactions on Internet and Information Systems.*, vol. 17, no. 1, pp. 51–73, Jan. 2023, doi: 10.3837/tiis.2023.01.004.
[39] B. Goyal *et al.*, "Detection of Fake Accounts on Social Media Using Multimodal Data With Deep Learning," *IEEE Transactions on Computational Social Systems.*, 2023, doi: 10.1109/TCSS.2023.3296837.
[40] O. A. Hanshal, O. N. Ucan, and Y. K. Sanjalawe, "Hybrid deep learning model for automatic fake news detection," *Applied Nanoscience*, vol. 13, no. 4, pp. 2957–2967, 2023, doi: 10.1007/s13204-021-02330-4.
[41] X. Gao *et al.*, "An Interpretable Fake News Detection Method Based on Commonsense Knowledge Graph," *Applied Sciences.*, vol. 13, no. 11, pp. 1–19, 2023, doi: 10.3390/app13116680.
[42] G. G. Devarajan, S. M. Nagarajan, S. I. Amanullah, S. A. S. A. Mary, and A. K. Bashir, "AI-Assisted Deep NLP-Based Approach for Prediction of Fake News from Social Media Users," *IEEE Transactions on Computational Social Systems.*, vol. 11, no. 4, pp. 4975–4985, 2024, doi: 10.1109/TCSS.2023.3259480.
[43] A. A. Ali, S. Latif, S. A. Ghauri, O. Y. Song, A. A. Abbasi, and A. J. Malik, "Linguistic Features and Bi-LSTM for Identification of Fake News," *Electronics (Switzerland)*, vol. 12, no. 13, pp. 1–16, Jul. 2023, doi: 10.3390/electronics12132942.
[44] S. Suryawanshi, A. Goswami, and P. Patil, "FakeIDCA: Fake news detection with incremental deep learning based concept drift adaption," *Multimedia Tools and Applications*, vol. 83, no. 10, pp. 28579–28594, 2024, doi: 10.1007/s11042-023-16588-z.
[45] M. Taha, H. H. Zayed, M. Azer, and M. Gadallah, "Automated COVID-19 misinformation checking system using encoder representation with deep learning models," *IAES International Journal of Artificial Intelligence.*, vol. 12, no. 1, pp. 488–495, 2023, doi: 10.11591/ijai.v12.i1.pp488-495.
[46] C. Mallick, S. Mishra, and M. R. Senapati, "A cooperative deep learning model for fake news detection in online social networks,"

Journal of Ambient Intelligence and Humanized Computing, vol. 14, no. 4, pp. 4451–4460, 2023, doi: 10.1007/s12652-023-04562-4.
[47] S. Wang, W. Yang, and Z. Li, "Towards fake news refuter identification: Mixture of Chi-Merge grounded CNN approach," *Expert Systems with Applications*, vol. 231, 2023, doi: 10.1016/j.eswa.2023.120712.
[48] Z. A. Jawad and A. J. Obaid, "the Combination of Convolution Neural Networks and Deep Neural Networks for Fake News Detection," *Journal of Engineering Science and Technology*, vol. 18, no. 1, pp. 814–826, Feb. 2023.
[49] R. Kozik, W. Mazurczyk, K. Cabaj, A. Pawlicka, M. Pawlicki, and M. Choraś, "Deep Learning for Combating Misinformation in Multicategorical Text Contents," *Sensors*, vol. 23, no. 24, pp. 1–13, 2023, doi: 10.3390/s23249666.
[50] M. Y. Chen, Y. W. Lai, and J. W. Lian, "Using Deep Learning Models to Detect Fake News about COVID-19," *ACM Transactions on Internet Technology*, vol. 23, no. 2, pp. 1–23, 2023, doi: 10.1145/3533431.
[51] M. Madani, H. Motameni, and R. Roshani, "Fake News Detection Using Feature Extraction, Natural Language Processing, Curriculum Learning, and Deep Learning," *International Journal of Information Technology and Decision Making*, vol. 23, no. 3, pp. 1063–1098, 2024, doi: 10.1142/S0219622023500347.

BIOGRAPHIES OF AUTHORS

Idza Aisara Norabid is a postgraduate student at Universiti Malaysia Terengganu, UMT (Ph.D.), and is working as a graduate research assistant under the research grant of Fundamental Research Grant Scheme (FRGS). She obtained both her Bachelor's degree in Computer Science and Master's degree in Computer Science (artificial intelligence) from Universiti Kebangsaan Malaysia (UKM). Her research interests are natural language processing and machine learning. She can be contacted at email: p5746@pps.umt.edu.my.

Masita Jalil is an Associate Professor at the Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu (UMT). She holds a Ph.D. degree in Information Systems from Universiti Kebangsaan Malaysia (UKM), a B.Eng. degree, and an M.Sc. degree from the University of Warwick, U.K. Her research interests primarily focus on software reuse, the application of software design artifacts in the field of software engineering which also extend to software maintenance and quality, as well as data and text mining. She has authored and co-authored over 50 journal articles and conference proceedings. Beyond research, she actively supervises local and international postgraduate students, imparting her expertise and shaping the next generation of scholars. She can be contacted at email: masita@umt.edu.my.

Rozniza Ali obtained her B.Sc. degree in Business Information System from the Kolej Ugama Sultan Zainal Abidin (KUSZA), Malaysia. She then received her M.Sc. degree in Information Technology from the Universiti Teknology MARA, Malaysia, and then finally received her Ph.D. degree in Computer Science from The University of Stirling, Scotland. She is currently a Senior lecturer at Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu (UMT). Her research area of interests comprises pattern recognition, machine learning, and image processing. She can be contacted at email: rozniza@umt.edu.my.

Noor Hafhizah Abd Rahim is currently an Associate Professor at the Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu (UMT). She holds a PhD in Artificial Intelligence from the University of Bristol, UK, and a Master's degree in Computer Science from the University of Malaya, Malaysia. She obtained her Bachelor's degree in Information Technology, majoring in Computer Science, from Universiti Kebangsaan Malaysia. Her research interests include artificial intelligence, machine learning, deep learning, and natural language processing. She can be contacted at email: noorhafhizah@umt.edu.my.