

An Extensive Review of Existing Machine Learning, Deep Learning and Transformer Based Approaches for Multilingual Sentiment Analysis

Er. Ritika Bhatia¹, Er. Komal Patiyal², Akshit³

P.G. Student, Department of Computer Science and Engineering, Himachal Pradesh Technical University, Hamirpur,
Himachal Pradesh, India¹

Faculty, Department of Computer Science and Engineering, Himachal Pradesh Technical University, Hamirpur,
Himachal Pradesh, India²

Faculty, Department of Computer Applications, Shree Hanumat Institute of Management and
Technology, Punjab, India³

ABSTRACT: With the recent explosion of social media and online space, the generation of large volumes of multilingual/code-mixed textual data has become a reality, and therefore multilingual sentiment analysis is an important area of research within the Natural Language Processing. However, the presence of language variations, the absence of annotated data, syntax, and semantics dissimilarities between languages is a severe issue to the successful sentiment classification. In the past couple of years, researchers have found alternative approaches such as traditional machine learning models and advanced deep learning and transformer-based frameworks. The paper will consist of an in depth review of the recent trends in the area of multilingual sentiment analysis, specifically machine learning, deep learning and transformer based algorithms. The paper will analyze the popular models, data sets and the techniques of assessment that have demonstrated the strength of hybrid deep learning and transformer models such as BERT, mBERT and XLM-RoBERTa in learning contextual and cross-linguistic representations. The key problems and research gaps are also expounded in order to give a boost to sentiment analysis in low resource and multilingual language environment.

KEYWORDS: Multilingual Sentiment Analysis, Machine Learning(ML), Deep Learning(DL), Transformer, Natural Language Processing (NLP).

I. INTRODUCTION

As the social media and online communication systems have rapidly developed, the volume of textual opinionated information has increased greatly and sentiment analysis is among the mandatory activities in Natural Language Processing (NLP). Sentiment analysis is identified as a method of automatically analyzing the opinions in text to identify whether they are positive, negative or neutral. The traditions of sentiment analysis are being put through the test of linguistic and situational diversity as the multilingual and code-mixed text abounds on the digital platforms. Recent papers have explored the multilingual sentiment classification task using transformer-based models such as multilingual BERT in the setting of enhanced cross-lingual understanding in social media data [1], and other articles have found the importance of multilingual transformer models in sentiment classification in low-resource languages [2]. It was also found in the comparative studies of the transformer architecture that the models such as XLM-RoBERTa and IndicBERT have better results when it comes to the classification of code-mixed sentiment [4]. Additionally, the study which analyzes the multilingual posts of the social media reveals that the transformer based model is capable of replicating the contextual sentiment patterns across the languages [6].

The studies that had been done before largely relied on traditional machine learning techniques such as Support Vector machine, Naive Bayes and Logistic regression that were modeled using feature engineering techniques. As an example, the studies of Hindi-English code-mixed corpora experiments indicated that SVM-based models can be applicable in the recognition of emotionality of multi-lingual texts [8]. Similarly, the analyses of multilingual comments in YouTube

and social media posts showed models of machine learning that determined the sentiment pattern within multilingual user comments [11]. The logistic regression-based model has also worked well in detecting sentiments of English-Punjabi code-mixed social media data [13]. Besides, the study is grounded on the Hinglish and multi-lingual conversational information, and it is related to the importance of pre-processing algorithms and language recognition when it comes to handling mixed-language text structures [15].

This has been enhanced by the recent advancements of deep learning and transformer-based architecture making multilingual sentiment analysis systems significantly more effective. Different neural network frameworks such as CNN, LSTM and GRU have been widely used to learn contextual dependencies and semantic relationships of multilingual data sets [17]. It has been demonstrated that CNN + LSTM hybrid deep learning models achieve superior sentiment classification scores in both social media commentaries and multilingual data sets [19]. Also, transformers-based models, such as BERT and mBERT, and XLM-RoBERTa, are shown to perform well at multilingual and cross-lingual sentiment classification tasks as they can obtain more contextual representations [21]. The ensemble and hybrid transformer models have been explored with the sentiment analysis of multilinguality using e-commerce reviews and social media dataset and high classification accuracy has been achieved in different languages [23], [25]. Based on these developments, the paper describes the works of machine learning, deep learning, and transformer-based models of multilingual sentiment analysis and the present research trends and research directions.

II. LITERATURE SURVEY

The literature review of the topic of multilingual sentiment analysis (with machine learning, machine deep, and transformer-based techniques) will be offered in this section. It is aimed at testing the methodologies, datasets, performance and languages of the models proposed previously. The survey also comes handy in establishing the trend of research that is present, limitations and the avenue that can be pursued in the future.

Machine Learning Approaches

The initial multilingual sentiment analysis has been widely performed in terms of traditional machine learning techniques. The strategies are commonly founded on feature extraction methods, such as TF-IDF, Bag-of-Words, and n-gram representations and classifier, such as Support Vector Machines, Naive Bayes, and Logistic Regression.

These models have been used in a number of studies on multilingual and code-mixed data where the objective of the study was sentiment classification. Incidentally, Hindi-English and multilingual social media text machine learning classifiers have been used to determine sentiment patterns [5] [11]. Similarly, logistic regression models have been used to classify the English-Punjabi code-mixed posts based on sentiment classification exercises [7]. In other literature, it has been highlighted that normalization, tokenization, and removal of stop-words play a crucial role in pre-processing of multilingual data to boost machine learning [8] [9].

Deep Learning Approaches

The deep learning approaches have sufficiently influenced sentiment analysis as a process of identifying contextual and semantic connections amongst textual data. The neural network designs that are generally used to learn more complex linguistic patterns on multilingual information include Convolutional Neural Networks (CNN), Long Short-Term memory (LSTM) and Gated Recurrent Unit (GRU).

Several papers have applied deep learning models to sentiment analysis tasks in two or more languages, as well as, code-mixed. Hybrid CNN-LSTM models have assisted in the enhancement of multilingual social media comment and online review sentiment classification [10] [14]. Similarly, the use of neural network design, involving LSTM and GRU, to detect emotions and sentiment patterns on the basis of multilingual text information has been researched [5]. In other articles, it is highlighted that deep learning models do not need extensive manual feature engineering to obtain meaningful textual features and are better than machine learning approaches of the past [23].

Transformer-Based Approaches

Transformer-based models have recently emerged as a result of their ability to generate rich contextual and cross-lingual representations as the most popular model to do multilingual sentiment analysis. Multilingual and code-mixed

text analysis Multilingual Multilingual text analysis Multilingual models such as BERT, multilingual BERT (mBERT) and XLM-RoBERTa have shown success in text analysis using multilingual and code-mixed text.

Transformer structures have been used in other works that classify sentiments in multilingual data. Speaking of the examples, the multilingual BERT may be used to consider the tendencies of sentiment analysis in multilingual posts on social media and code-mixed texts [1] [2]. The other comparative studies have also shown that the transformer models such as XLM-RoBERTa and other multilingual transformers were shown to be more effective when it comes to multilingual sentiment classification tasks compared to the traditional machine learning and deep learning models [4] [13]. Also, the transformer-based systems have been successfully applied in other applications like social media, financial texts analysis, and multilingual review datasets that is also effective in processing complicated linguistic structures of languages [3] [21].

Hybrid Approaches

In addition to the classic machine learning, deep learning, and transformer-based model, several studies have explored the use of a hybrid and ensemble model in order to improve sentiment analysis in multilingual. These approaches are an integration of other approaches to apply the benefits of other models and to enhance the classification results.

As a hint, hybrid deep learning frameworks, consisting of CNN and LSTM frameworks, have been proposed to acquire local and contextual textual indications on multilingual data [6] [7]. Combinations between models of transformers and other neural architecture-based ensembles have also been explored to improve the accuracy of sentiment classification of multilingual review data [8]. Other studies have also included explainable AI techniques and optimization strategies to enhance the interpretability and the output of the models invoked to accomplish tasks of multilingual sentiment analysis [3] [12].

III. MULTILINGUAL SENTIMENT ANALYSIS GENERAL METHODOLOGY

The section describes the general methodological pipeline that is usually followed in the multi-lingual sentiment analysis systems. Most of the studies have adopted a series of steps irrespective of whether he is using machine learning, deep learning or transformer based models.

Data Collection

The first stage of multilingual sentiment analysis is to collect textual data in multiple sources which include social media, product reviews as well as forums. In numerous works, multilingual datasets of user-generated content are actively used to investigate the trends in sentiments in different languages and domains [1] [5] [11]. Social media posts or financial news are also used to collect domain-specific data in other works to make sentiment classification models [21].

Data Pre-processing

Before the model training, the process involving textual data involves cleaning the data to remove any noise present and improving the quality of the data. The most popular preprocessing steps include tokenization, removal of stop-words, text normalization and language identification. The techniques are of particular importance in the working with multilingual and code-mixed text where spelling variability and informal style of writing are commonly observed [7] [8] [9].

Feature Representation

The textual data gets processed and then they are converted to numerical values that can be inputted into the machine learning or the deep learning models. Traditional approaches are founded on feature extraction schemes, e.g., TF-IDF and Bag-of-Words, and newer approaches are based on word embeddings, such as Word2Vec and contextual embeddings (generated by a transformer model) [4] [13] [17]. These are semantic and contextual representations which are valuable in capturing the multilingual text semantic and contextual relationships.

Model Training

In this step, the feature or embedding that is extracted are trained to create sentiment classification models. Machine learning models can be used by different researchers, such as SVM and Logistic Regression, deep learning models

include CNN and LSTM, and transformer-based ones, such as BERT and XLM-RoBERTa [2] [10] [23]. The training data are used to develop patterns on which the trained models predict sentiment of unseen multilingual text.

Sentiment Classification and Evaluation.

And finally, the trained model will predict the polarity of the sentiment of the input text (usually positive, negative or neutral). The accuracy, precision, recall, and F1-score are the measures used to test the model regarding the efficiency of the sentiment analysis system [3] [14] [25].

IV. SUMMARY

Multilingual sentiment analysis is a subject of significant concern that has been given importance by the increasing occurrence of multilingual and code-mixed textual resources on the online platforms. The traditional machine learning algorithms such as Support Vector Machines and Logistic Regression were mostly used in initial studies to perform sentiment classification problems [5] [7]. With the evolution of the deep learning sphere, such neural networks as CNN and LSTM have gained popularity in identifying the contextual links between the multilingual texts data [10] [23]. More recently, transformer-based models, including BERT, mBERT and XLM-RoBERTa have performed more successfully in multilingual sentiment analysis due to their ability to acquire contextual and cross-lingual representations [1] [4] [13]. The studies of the hybrid and ensemble approaches to realizing further progress in the classification performance over multilingual datasets have also taken place [6] [8]. Though this has been done, there are still challenges such as the unavailability of annotated datasets, the existence of code-mixing and linguistic diversity that continue to impact the performance of the multilingual sentiment analysis systems [9] [21].

V. CONCLUSION

The multilingual sentiment analysis has taken its place as an important area of study in relation to the rapidly increasing multilingual and code-mixed textual data on the social media, as well as on the online sources. The review discussed the available literature that is based on machine learning, deep learning, and transformer-based models. In the discussion, we can see how the classical machine learning models were developed until the highest level, the deep learning and transformer models that have the advantage of more situational awareness and better sentiment recognition rate.

Although the multilingual sentiment prediction task has massively been improved with the advent of new models, several difficulties, including the lack of annotated data, code-mixing problems, and processing of low-resource languages, persist. The future research directions of my study would also be to develop more potent cross-lingual models, bigger multilingual benchmark sets, and efficient architectures capable of executing varied linguistic designs on a reduced expenditure of computations.

Table 1: Comparative Analysis of Multilingual Sentiment Analysis Studies

Ref.	Dataset(s)	Languages	Approach	Model(s)	Embeddings	Accuracy/Performance Improved
[1]	Synthetic multilingual social media dataset	English, Hindi, Spanish	Transformer	Multilingual BERT (mBERT)	Contextual embeddings	~91%
[2]	CMDSA-24 Code-Mixed Dataset (social media comments)	Roman Urdu, Roman Punjabi, English	Transformer	CMSA-mBERT (fine-tuned multilingual BERT)	BERT embeddings, transformer tokenization	~22% improvement over baselines
[3]	Banking customer reviews dataset	English, Sinhala, Singlish,	Hybrid Transformer	XLM-RoBERTa + BERT-	Contextual embeddings, domain-	92.3% (English), 88.4% (Sinhala/code-mixed)

		Sinhala-English code-mixed		base-uncased + lexicon refinement	specific lexicons, SHAP, LIME	
[4]	Hinglish social media dataset (Twitter, Facebook, WhatsApp messages)	Hindi, English	Hybrid (ML + DL + Transformer)	SVM, Naive Bayes, LSTM, BERT	n-gram features	-
[5]	Code-mixed Indic sentiment datasets (Hinglish, Punglish, Tanglish tweets)	Hindi-English, Punjabi-English, Tamil-English	Transformer	GPT-2, RoBERTa, XLM-RoBERTa, IndicBERT	Token embeddings, contextual embeddings	96.86% (Hinglish), 96.95% (Punglish), 97.55% (Tanglish)
[6]	YouTube code-mixed comments dataset	Hindi, English	ML/DL	Logistic Regression, SVM, Naive Bayes, Random Forest, LSTM, BiLSTM, GRU, CNN	Text embeddings, tokenized text features	81.40% (SVM best)
[7]	Multilingual movie review dataset	Multiple languages	Hybrid DL	CNN-LSTM optimized using Grey Wolf Optimization (GWO)	Language-specific word embeddings	+9.51% over ML models, +5.42% over DL baselines
[8]	GERD Twitter dataset	English, Amharic, Arabic	Hybrid DL + Transformer embeddings	mBERT + LSTM + CNN	Multilingual BERT embeddings, tokenized tweet features	95.3% training, 92% testing accuracy
[9]	Multilingual Amazon Reviews Corpus (MARC)	Multiple languages (Amazon multilingual reviews)	Hybrid Transformer + DL	T5 + Capsule Network (CapsNet) Meta-Ensemble	Contextual embeddings, hierarchical sentiment features, GAN-based data augmentation	97.56%

[10]	Multiple multilingual sentiment datasets	Multiple languages	Review (DL + Transformer + Ensemble)	XLM-R, LaBSE, MPNet, mBERT, DistilBERT	Contextual embeddings, ensemble learning methods (bagging, boosting, stacking)	-
[11]	CodeSwitched-YTSentiment dataset	Tamil, English, Tanglish (Tamil-English)	Hybrid ML + Transformer embeddings	Voting Classifier (Logistic Regression + Random Forest + SVM) with mBERT & XLM-RoBERTa	Multilingual embeddings, hybrid tokenization	97%
[12]	English-Punjabi Code-Mixed Social Media Dataset	English, Punjabi	ML	Logistic Regression classifier	TF-IDF	92%
[13]	MR dataset, SST-2 dataset, CoLA dataset	English	Hybrid Deep Learning + Transformer	MFFMP-ETC (mBERT + BiLSTM + TextCNN + multi-feature fusion)	Contextual embeddings, multi-view representation fusion, bidirectional semantic modeling	-
[14]	YouTube trending comments dataset	Bengali, English	Hybrid DL	CNN-LSTM	GloVe word embeddings	90.95% (Bangla), 97.42% (English)

[15]	E-commerce review dataset	Multiple languages (multilingual reviews)	Hybrid DL + Transformer embeddings	GPT-3.5 + CNN + BiLSTM + Self-Attention	GPT-3.5 contextual embeddings, CNN feature extraction, self-attention weighting	-
[16]	WhatsApp Chat Dataset	Hindi, English	Hybrid DL + Lexicon	VADER + LSTM	VADER sentiment scores, LSTM embeddings	97.89%
[17]	Airline Twitter Sentiment Dataset (airline customer feedback tweets)	English	Transformer + DL	BERT + MLP	Contextual BERT embeddings, TF-IDF features	-
[18]	Student-People Mass Uprising Public Sentiments Dataset	Bangla	Hybrid Transformer + ML	XMB-BERT (BanglaBERT + mBERT + XLM-RoBERTa) with Voting Classifier	Transformer embeddings	83.7%
[19]	Multilingual Fake News datasets	Hindi, Tamil, English	Hybrid DL + Transformer	LSTM + BERT classifier	Semantic embeddings, TF-IDF features, NMF dimensionality reduction, contextual embeddings	97% (Hindi), 93% (English), 84% (Tamil)

[20]	Twitter Sarcasm / Irony Detection Dataset	English	Hybrid Deep Learning	CNN + BiLSTM / Deep hybrid sentiment model	Word embeddings, semantic feature extraction, contextual sequence learning	-
[21]	Financial market datasets (Yahoo Finance price data, financial news, Twitter, Reddit text data)	Multilingual financial text	Hybrid DL + Transformer	LSTM + Transformer (RoBERTa, FinBERT, XLM-RoBERTa)	Numerical market indicators, sentiment scores from FinBERT, multilingual contextual embeddings, tokenization via RoBERTa	-
[22]	Dravidian Code-Mix Dataset (DravidianLangTech 2021) and Tamil-English social media comments	Tamil, Tamil-English	Hybrid DL + Transformer	VNN + BERT	Character n-grams, TF-IDF, Bag-of-Words, Word2Vec embeddings, contextual transformer embeddings	-
[23]	8 datasets of tweets and review texts	English, Hindi	Hybrid DL	CNN + LSTM + SVM	Word2Vec embeddings, BERT embeddings, CNN feature extraction, sequential learning via LSTM	+11.6% improvement over baseline models
[24]	Twitter tweets and review datasets	English, Hindi	Hybrid Deep Learning	CNN + LSTM	Word embeddings, sentiment dictionary features, morphological analysis	-

[25]	Hinglish dataset, Punglish dataset, English sentiment dataset	Hindi-English, Punjabi-English, English	Transformer	Shared-Private BERT Multi-Task Framework	BERT contextual embeddings, shared-private feature representation	-
------	---	---	-------------	--	---	---

REFERENCES

[1] G. Bandrupalli, “Enhancing sentiment analysis in multilingual social media data using transformer-based NLP models: A synthetic computational study,” TechRxiv Preprints, 2025. doi: 10.36227/techrxiv.174440282.23013172/v1.

[2] M. K. Nazir, C. N. Faisal, M. A. Habib, and H. Ahmad, “Leveraging multilingual transformer for multiclass sentiment analysis in code-mixed data of low-resource languages,” IEEE Access, vol. 13, pp. 7538–7554, 2025. doi: 10.1109/ACCESS.2025.3527710.

[3] A. Rizvi, N. Thamindu, W. P. U. Senevirathna, A. M. N. H. Adhikari, D. Kasthurirathna, and L. Abeywardhana, “Enhancing multilingual sentiment analysis with explainability for Sinhala, English, and code-mixed content,” arXiv Preprint, 2025. doi: 10.48550/arXiv.2504.13545.

[4] P. Tewaria, S. Tyagi, M. Gumber, and P. Seekhwal, “Hinglish text analysis: Challenges and opportunities in multilingual natural language processing,” in Proc. Int. Conf. Innovative Computing & Communication (ICICC), 2024. doi: 10.2139/ssrn.5193470.

[5] M. P. K. T., G. Shrinithi, P. Nithish, and A. C. Panesh, “Comparative analysis of transformer models for sentiment classification in code-mixed Indic languages,” Int. J. Eng. Res. Sustain. Technol., vol. 3, no. 1, pp. 1–9, Mar. 2025. doi: 10.63458/ijerst.v3i1.101.

[6] R. Mahajan, A. S. More, and U. Shah, “Navigating emotion in code-mixed languages: Performance of ML and DL models on Hindi-English text,” in Proc. Int. Conf. Machine Learning and Data Engineering, 2025. doi: 10.1016/j.procs.2025.04.654.

[7] V. Jain, L. Malviya, and A. S., “Optimized hybrid deep learning for cross linguistic sentiment analysis: A novel approach,” J. Cloud Computing, 2025. doi: 10.1186/s13677-025-00753-w.

[8] A. M. Mekonnen, Y. Y. Munaye, and Y. B. Chekol, “Hybrid LSTM-CNN approach using multilingual BERT for sentiment analysis of GERD tweets,” Buletin Ilmiah Sarjana Teknik Elektro, vol. 7, no. 2, pp. 206–213, Jun. 2025. doi: 10.12928/biste.v7i2.13281.

[9] N. N. I. Prova, “Multilingual emotion classification in e-commerce customer reviews using GPT and deep learning-based meta-ensemble model,” SSRN Preprint, 2025. doi: 10.2139/ssrn.5161505.

[10] E. A. Elhadidi, A. Salah, M. Abdella, and S. M. Darwish, “Multilingual sentiment analysis: A review of deep learning transformer models and ensemble techniques,” Int. J. Computers and Informatics, vol. 7, pp. 91–103, 2025. doi: 10.21608/jocc.2025.446637.

[11] D. N., M. M., A. C. S., L. R., T. M., and S. N., “Ensemble-driven multilingual sentiment analysis framework for YouTube comments with dashboard,” in Proc. Int. Conf. Visual Analytics and Data Visualization (ICVADV), 2025. doi: 10.1109/ICVADV63329.2025.10961107.

[12] A. Tiwari, J. Sehgal, M. Singh, and A. Mishra, “Sentiment analysis in English-Punjabi mixed social media posts,” in Proc. IEEE Int. Conf. Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), 2025. doi: 10.1109/IATMSI64286.2025.10985051.

[13] R. Zhang, “Multilingual pretrained based multi-feature fusion model for English text classification,” Computer Science and Information Systems, vol. 22, no. 1, pp. 133–152, 2025. doi: 10.2298/osis240630004z.

[14] S. R. R. Rahman, J. U. Tanvin, and M. N. Islam, “A hybrid deep learning model for sentiment analysis of multilingual comments on trending YouTube videos,” in Proc. Int. Conf. Electrical, Computer and Communication Engineering (ECCE), 2025. doi: 10.1109/ECCE64574.2025.11013083.

[15] J. Benita, S. Shamyuktha, M. K. Devi, and P. Vineela, “Breaking language barriers in mental health: A multilingual chatbot for global support,” in Proc. Int. Conf. Computational Robotics, Testing and Engineering Evaluation (ICCRTEE), 2025. doi: 10.1109/ICCRTEE64519.2025.11052936.

- [16] D. Sinha, V. Jain, and A. N. Pandey, "Sentiment analysis of code-mixed WhatsApp conversations (Hinglish): A hybrid approach," in Proc. IEEE Int. Conf. Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), 2025. doi: 10.1109/IATMSI64286.2025.10985128.
- [17] V. S. and C. Bagyalakshmi, "Twitter data based on airline feedback using BERT (Bi-directional encoder representations from transformers)," in Proc. Int. Conf. Data Science and Business Systems (ICDSBS), 2025. doi: 10.1109/ICDSBS63635.2025.11031788.
- [18] M. S. Hossena, M. Saiduzzamana, and P. Shahab, "Social media sentiments analysis on the July revolution in Bangladesh: A hybrid transformer-based machine learning approach," in Proc. Int. Conf. Electronics, Computers and Artificial Intelligence (ECAI), 2025. doi: 10.1109/ECAI65401.2025.11095452.
- [19] M. Tummala, M. E. Malkhed, and S. Vekkot, "Hybrid semantic and contextual analysis for multilingual fake news detection using deep learning," in Proc. Int. Conf. Disruptive Technologies (ICDT), 2025. doi: 10.1109/ICDT63985.2025.10986464.
- [20] J. Sengathir, M. D. Priya, A. C. J. Malar, and V. Vijayagopal, "Hybrid deep learning model for accurate detection of irony and sarcasm from Twitter dataset," in Proc. Int. Conf. Soft Computing for Security Applications (ICSCSA), 2025. doi: 10.1109/ICSCSA66339.2025.11170730.
- [21] T. S. Akhila, J. R. F. Raj, D. K. Jesintha, R. S. Krishnan, and P. S. Vadivel, "Hybrid deep learning for international trading: Integrating LSTM and transformer models," in Proc. Int. Conf. Sentiment Analysis and Deep Learning (ICSADL), 2025. doi: 10.1109/ICSADL65848.2025.10933130.
- [22] J. M., P. S., and M. K., "Automated identification of offensive language in code-mixed social media content using a hybrid VNN-BERT model," in Proc. Int. Conf. Expert Clouds and Applications (ICOECA), 2025. doi: 10.1109/ICOECA66273.2025.00026.
- [23] [M. Wang, Q. Hou, and A. Peng, "Enhancing sentiment analysis in e-commerce through the integration of GPT-3.5 embeddings and BiLSTM networks," in Proc. IEEE Int. Conf. Systems, Man, and Cybernetics (SMC), 2024. doi: 10.1109/SMC54092.2024.10831751.
- [24] R. Negi, A. Ashraf, and S. S. Sehgal, "Hybrid deep learning model for multilingual sentiment analysis," in Proc. IEEE Karachi Section Humanitarian Technology Conference (KHI-HTC), 2024. doi: 10.1109/KHIHTC60760.2024.10481942.
- [25] M. Mamta and A. Ekbal, "Transformer based multilingual joint learning framework for code-mixed and English sentiment analysis," Journal of Intelligent Information Systems, vol. 62, pp. 231–253, 2024. doi: 10.1007/s10844-023-00808-x.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details