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Research Article

A Hybrid Deep Learning Approach for Efficient Cross-Language Detection

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Abstract:

Cross-language detection is a challenging task that involves identifying the language of a given text across multiple languages, often in noisy or mixed-language environments. This also identify and classify text across different languages for various applications, such as multilingual sentiment analysis, language translation and cross-border content moderations. Traditional approaches often rely on rule-based systems or monolingual models, which lack scalability and adaptability to diverse linguistic structures. In this study, we propose a hybrid deep learning model combining Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks to enhance language detection accuracy and robustness. LSTM and GRU, known for their ability to capture long-term dependencies and reduce vanishing gradient problems, are integrated to leverage their complementary strengths. The model is evaluated using BLEU scores, a widely accepted metric for evaluating linguistic quality, and perplexity, which measures the model's ability to predict a sequence of words. Our experimental results demonstrate that the hybrid deep learning model outperforms traditional approaches, achieving high BLEU scores and low perplexity across diverse multilingual datasets. This approach not only improves language detection accuracy but also reduces computational complexity, making it suitable for real-time applications in multilingual text processing. The proposed model shows promise in real-world applications, enabling efficient cross-language detection in multilingual environments.

1. Introduction

In today's interconnected world, the need for efficient and accurate cross-language detection systems has become essential. The proliferation of multilingual content across various platforms, including social media, e-commerce, and online communication tools, demands robust language identification systems to enhance user experiences, enable effective communication, and ensure the accuracy of downstream natural language processing (NLP) tasks [1]. Traditional language detection systems often struggle in noisy, code-switched, or resource-limited environments, necessitating innovative approaches that can handle the complexities of multilingual data.

Language detection involves classifying text into one of several predefined languages based on linguistic patterns, vocabulary, and syntax. While conventional statistical and rule-based approaches have achieved moderate success, they often fail to capture the contextual nuances and long-range dependencies present in natural language.

Machine learning techniques, particularly deep learning models, have demonstrated significant improvements in various NLP tasks by learning complex patterns directly from data, eliminating the need for extensive handcrafted features [2-4]. However, the challenge of handling diverse and dynamic multilingual datasets requires more sophisticated models capable of capturing both short- and long-term dependencies in textual sequences.

Recurrent Neural Networks (RNNs) have been widely adopted for sequence-based tasks due to their ability to process input sequences of arbitrary length [5]. However, standard RNNs suffer from vanishing and exploding gradient problems, making them less effective in modelling long-term dependencies.

To overcome these limitations, advanced variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have been introduced. LSTM networks utilize memory cells and gating mechanisms to retain relevant information over long sequences, while GRU networks offer a simplified architecture with comparable performance, reducing computational overhead [6-7]. Both architectures have become popular choices for NLP tasks, including language detection. Despite the individual strengths of LSTM and GRU models, each has its limitations. LSTM models are more computationally intensive, while GRUs, although efficient, may not capture complex patterns as effectively in certain contexts [8]. This motivates the need for a hybrid approach that leverages the advantages of both models.

By combining LSTM and GRU networks, a hybrid deep learning model can capture long-range dependencies with higher precision and efficiency, making it well-suited for cross-language detection tasks where language patterns vary significantly. To evaluate the performance of language detection models, metrics such as BLEU (Bilingual Evaluation Understudy) score and perplexity are widely used. BLEU is a precision-based metric originally designed for machine translation evaluation but is increasingly applied in tasks involving sequence modelling and text generation [9-10].

A higher BLEU score indicates better language sequence prediction and alignment with the target language. Perplexity, on the other hand, measures how well a probabilistic model predicts a sequence of words [11]. Lower perplexity scores indicate better generalization and model performance, especially in diverse language datasets.

In this study, we propose a hybrid LSTM-GRU model to enhance cross-language detection accuracy and efficiency. We evaluate the model on multilingual datasets, using BLEU scores and perplexity as performance metrics. Our results show that this hybrid model significantly outperforms traditional single-model architectures, achieving superior accuracy and reduced computational complexity. This approach demonstrates potential for real-time applications in various multilingual environments, such as automatic content moderation, sentiment analysis, and machine translation preprocessing.

1.1 Contribution of the research

1.This research introduces a hybrid deep learning model combining LSTM and GRU networks to enhance cross language detection by leveraging their complementary strengths in handling long and short term dependencies.

2.The proposed model addresses the challenges of language identification in noisy, codeswitched, and resource constrained environments, improving robustness and accuracy in multilingual datasets.

3.The hybrid LSTMGRU model reduces computational overhead while maintaining high detection performance, making it suitable for real time applications in multilingual environments.

4.The research evaluates the hybrid model using BLEU scores and perplexity, providing a comprehensive analysis of its linguistic prediction accuracy and sequence modelling efficiency.

2. Related Work

Noor et al. [12] proposed a hybrid deep learning model for real-time Arabic Sign Language (ArSL) recognition to address the lack of sign language interpreters in Saudi Arabia, which restricts communication accessibility for the hearing-impaired population. The study focused on developing a system capable of recognizing both static and dynamic gestures in ArSL by combining a Convolutional Neural Network (CNN) for extracting spatial features and a Long Short-Term Memory (LSTM) network for capturing spatio-temporal aspects. The dataset consisted of 4000 images for 10 static gesture words and 500 videos for 10 dynamic gesture words, achieving accuracy rates of 94.40%

with the CNN and 82.70% with the LSTM classifiers. Despite the promising results, the model's performance for dynamic gestures was comparatively lower, indicating a need for further refinement in handling temporal variations. Additionally, the system's real-time application feasibility in diverse lighting conditions and with varying signer profiles remains a challenge, warranting additional research for practical deployment.

Geethanjali et al. [13] proposed a novel hybrid deep learning model, IChOA-CNN-LSTM, to address the complexities of multimodal emotion recognition in social media during the COVID-19 pandemic. Their research integrates data from multiple modalities, including text, images, audio, and videos from platforms like Twitter, offering a more comprehensive approach to sentiment analysis compared to conventional methods, which predominantly focus on text data. The IChOA-CNN-LSTM model combines Convolutional Neural Networks (CNNs) for image feature extraction, Long Short-Term Memory (LSTM) networks for sequential data analysis, and an Improved Chimp Optimization Algorithm (IChOA) for effective feature fusion, achieving an impressive 97.8% accuracy rate. This model leverages the GeoCoV19 dataset to facilitate analysis across linguistic and geographical boundaries, offering valuable insights for public health decision-making. Despite its successes, the model's reliance on multiple modalities may pose challenges in data collection and processing, requiring significant computational resources and potentially facing difficulties in handling highly imbalanced datasets.

Kazbekova et al. [14] proposed a Hybrid Deep Learning Architecture (HDLA) for offensive language detection on online social networks (OSNs). In the digital age, OSNs have become major communication platforms, but they also facilitate the spread of offensive language, contributing to hate speech, cyberbullying, and discrimination, which deteriorate the quality of online interactions. The HDLA model integrates Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks, leveraging the strengths of both techniques. CNNs excel in extracting spatial features within text data, while LSTMs capture the temporal dependencies and contextual nuances of user posts. This dual approach improves the detection of both overt and covert offensive content, offering high accuracy in various OSN environments. The model outperforms traditional natural language processing methods in terms of precision, recall, and F1-score, and maintains interpretability, providing insights into the propagation of offensive content. However, the model's performance may still be limited by the inherent complexity and variability of language use, especially in the context of rapidly evolving slang and non-standard expressions, which can pose challenges for precise detection.

Yahya et al. (2022) [15] propose a novel approach to cross-language source code clone detection using a deep learning model, Infer Code, which leverages abstract syntax tree (AST) embeddings to analyze source code in an end-to-end manner without relying on manual feature engineering. Their method, designed to overcome challenges posed by varying lexical structures of different programming languages, employs a Siamese neural network architecture to address data scarcity and mitigate overfitting. The model is evaluated based on its precision, recall, and F-measure, achieving 0.99, 0.59, and 0.80, respectively, demonstrating its superiority over existing single-language clone detection methods. However, the relatively lower recall score highlights a limitation in identifying all relevant clones, indicating room for improvement in handling complex scenarios or diverse datasets.

Ullah et al. [16] proposed CroLSSim, a novel tool for detecting cross-language software similarity using a hybrid approach that integrates Abstract Syntax Tree (AST)-based Method Description (MDrep) features with a CNN-LSTM model. The study addresses the challenge of identifying similar software applications across different programming languages, each with unique syntactic and semantic structures. AST features, representing the abstract structure of programming codes, are combined with MDrep to examine relationships among method calls. The approach incorporates Term Frequency-Inverse Document Frequency for local and global weight computation, followed by Latent Semantic Analysis for dimensionality reduction and semantic anchor extraction. Deep features are mined using CNN, and a hybrid CNN-LSTM model is employed for similarity detection. The dataset comprises approximately 9.5K Java, 8.8K C#, and 7.4K C++ programs from GitHub, demonstrating superior performance compared to state-of-the-art methods. However, the reliance on GitHub repositories for dataset creation could introduce bias, as it may not comprehensively represent diverse programming styles and domains. Additionally, the computational complexity of the hybrid model could limit its scalability for real-time applications.

Li et al.[17] proposed a twin network model for cross-linguistic similarity evaluation, incorporating ordered neuron long- and short-term memory neural networks as subnets. The model fuses bilingual word embeddings and encodes input sequence representations using these networks. It further constructs the distributed semantic vector representation of sentences by leveraging the global modelling capability of a fully connected network for higher-order semantic extraction. The final output represents the similarity between bilingual sentences, optimized through the adjustment of parameters across each layer in the framework. Experimental results demonstrated that the model achieved an accuracy of 81.05%, significantly improving the accuracy of text similarity and offering faster convergence, thus enhancing semantic text analysis. However, the model's performance could be affected by the quality and scope of the bilingual word embeddings used, and it may not generalize well to languages with limited resources or highly complex linguistic structures.

Vijayakumar et al. [18] proposed a hybrid deep learning model for multimodal cyberbullying detection, focusing on both text and image data. The model combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to detect cyberbullying in various forms of online content, such as text-based messages and images. This approach leverages the power of deep learning to detect harmful behaviours across these two modalities, utilizing publicly available datasets and testing the system with Telegram chat data. The paper highlights the importance of detecting cyberbullying through both text and images, as these are key mediums used in online harassment. Despite the promising results, one drawback of this study is that it does not address the integration of video data, which could further enhance the detection capabilities and provide a more comprehensive solution to combat cyberbullying in diverse online contexts.

Rosenthal et al. [19] introduced SOLID, a large-scale semi-supervised dataset for offensive language identification, addressing the limitations of previous datasets like OLID. While OLID provided a hierarchical annotation taxonomy for offensive language, including categories such as hate speech, cyberbullying, and cyber-aggression, its size was restricted, especially for low-level categories with only a few hundred instances, which posed challenges for training deep learning models. In contrast, SOLID includes over nine million English tweets, labeled in a semi-supervised manner, and demonstrates improved model performance when combined with OLID, particularly for lower-level categories of offensive language. Despite its contributions, the semi-supervised labelling approach may still lead to potential inaccuracies or biases in the data, which could affect the overall performance of models trained on this dataset.

Deepti Deshwal et al. [20] propose a Language Identification (LID) system leveraging hybrid robust feature extraction techniques and feedforward back-propagation neural networks (FFBPNN) in their work, "A Language Identification System using Hybrid Features and Back-Propagation Neural Network" (2020). The study evaluates the performance of individual features such as Mel frequency cepstral coefficients (MFCC), perceptual linear prediction (PLP), and relative perceptual linear prediction (RASTA-PLP), as well as hybrid combinations like MFCC + PLP and MFCC + RASTA-PLP. The classification phase employs two learning algorithms, Levenberg–Marquardt (trainlm) and scaled conjugate gradient (trainscg), with hybrid features demonstrating superior accuracy compared to individual features. Among hybrid techniques, MFCC + RASTA-PLP achieves the highest accuracy of 94.6% with a minimum test error rate of 0.10, validated using MATLAB simulations on a user-defined language database. However, a notable drawback is the study’s reliance on a custom language dataset, limiting the generalizability and scalability of the findings to diverse real-world datasets.

3. Proposed Methodology

3.1 Data Collection

In cross-language detection using a hybrid LSTM-GRU model, we utilized two diverse datasets to ensure the model’s robustness across different linguistic contexts. The first dataset is a multilingual dialogue dataset, which consists of conversational data in multiple languages, including English, Spanish, French, and Hindi, among others. This dataset captures natural language dialogues from a variety of sources such as social media, customer support interactions, and multilingual chat logs, providing a rich source of data for detecting code-switching and mixed-language dialogues [21]. The second dataset is an English-to-Telugu parallel dataset, specifically designed for language identification and machine translation tasks. It contains aligned sentences in both English and Telugu, providing a clean, structured resource for training and evaluating language detection in contexts where English and Telugu are used together. The combination of these datasets allows the model to learn not only from monolingual and bilingual scenarios but also from more complex, real-world multilingual data, ensuring it can handle a wide array of language combinations and switching patterns.

3.2 Data Preprocessing

In our research on cross-language detection using a hybrid deep learning model (LSTM and GRU), we employed a comprehensive set of data preprocessing techniques to ensure the input data was clean, consistent, and optimized for model performance.

- Text cleaning and normalization involved removing special characters, symbols, punctuation, URLs, emails, and non-linguistic tokens, converting all text to lowercase, and expanding contractions (e.g., “don’t” to “do not”) to maintain uniformity.
- Stopwords were selectively handled—language-specific stopwords were retained if they contributed to language identification, while others were removed to reduce noise.
- To handle multilingual scripts effectively, all text data was standardized to UTF-8 encoding.
- For text vectorization, we used multiple techniques: One-Hot Encoding for small vocabularies, pretrained multilingual word embeddings such as GloVe and fastText for capturing semantic relationships, and character-level embeddings for complex scripts or short texts.
- Additionally, numerical features like sentence length and punctuation frequency were normalized using Min-Max Scaling and Standardization to prevent disproportionate influence on the model.

These preprocessing steps were crucial in enhancing the model’s ability to handle diverse multilingual datasets, ensuring robust and accurate language detection.

3.3 Long Short-Term Memory

Long Short-Term Memory (LSTM) is a specialized type of recurrent neural network (RNN) that is designed to address the limitations of traditional RNNs, particularly in handling long-range dependencies. Standard RNNs face challenges when learning from sequences with long-term dependencies due to issues like vanishing gradients, where the influence of earlier data diminishes as the network processes further inputs. LSTMs overcome this problem by incorporating a memory cell and gating mechanisms, which control the flow of information within the network [23]. These mechanisms—input, forget, and output gates—allow LSTMs to decide which information should be remembered, updated, or discarded at each time step. As a result, LSTMs are particularly effective in tasks such as time-series forecasting, speech recognition, and natural language processing, where context and past information are crucial [22]. Their ability to model complex sequential patterns has made them a cornerstone in deep learning applications that involve sequential or temporal data. The entire framework of LSTM is depicted in Figure 1.

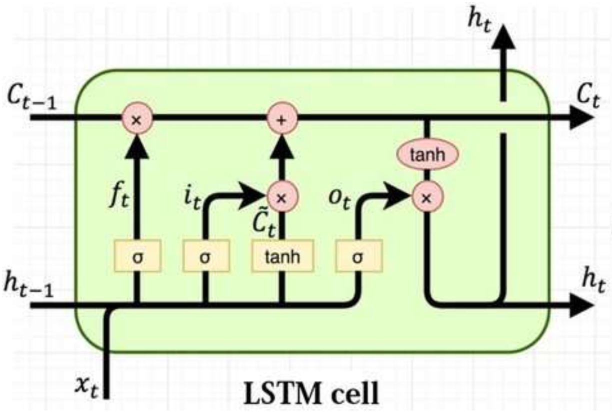

Figure 1. *Architecture for Long Short-Term Memory*

Forget gate – The forget gate decides what information and how much information to erase from the cell state. The information in the cell state ct−1 is altered through an elementwise multiplication of the forget gate’s output ft 2. The forget gate’s activation function is the sigmoid function; this ensures that the output vector from the gate yields continuous values between 1 (keep) and 0 (forget). The subscript ‘f ’ on the matrix and bias in equation 1 indicates their belongingness to the forget gate.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$c_f = c_{t-1} \times f_t \quad (2)$$

Input gate – The next important gate is the input gate. This gate uses two functional units. The first functional unit use a tanh activation which output values between -1 and 1 and decide the change of the cell state ˜ct. The latter use a sigmoid activation function, and it is responsible for the magnitude of the change mt. After multiplying the results of these two functional units, the input gate adds the result to the cell state, equation 5, and this completes the update of the cell state.

$$c\tilde{}t = \tanh(Wc \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

$$m_t = \sigma(Wm \cdot [h_{t-i}, x_t] + b_m) \quad (4)$$

$$c_t = c_f + \tilde{}ct * m_t \quad (5)$$

Output gate – The output gate uses a trained matrix Wo and bias bo, to fetch relevant information from the current input and previous output, equation 6. This information is combined with the newly adjusted cell state ct to predict the next output, ht, equation 7. This output recurs such that the next iteration can use it. If there are multiple layers, this output is also used as input in the next layer, if not this output is the prediction.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_{LSTM} = o_t * \tanh(c_t) \quad (7)$$

3.4 Gated Recurrent Unit

Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) designed to address some of the same challenges as Long Short-Term Memory (LSTM), particularly in modelling long-range dependencies in sequential data [24-25]. GRUs are a simpler alternative to LSTMs with fewer parameters while maintaining similar performance in many tasks. The key innovation in GRUs lies in the use of two gates—update and reset gates—that control the flow of information. The update gate determines how much of the previous memory should be carried forward to the current time step, while the reset gate decides how much of the previous memory should be discarded when computing the new candidate memory. These gates help the network decide when to update its internal state and when to reset the memory, allowing it to capture both short-term and long-term dependencies efficiently. The Architecture of GRU is depicted in Figure 2.

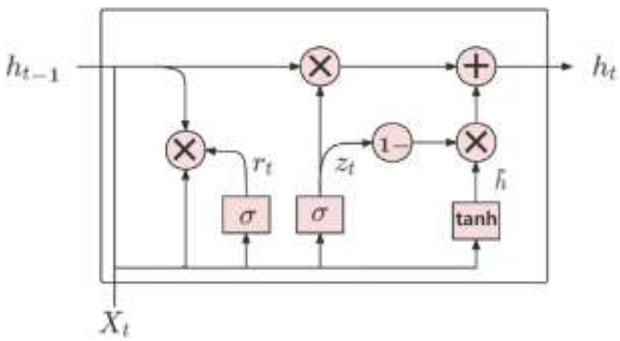

Figure 2. *Architecture for Gated Recurrent Unit*

The equations governing the GRU are as follows:
1. Update Gate: This gate controls the extent to which the previous hidden state is retained.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (8)$$

where zt is the update gate, σ is the sigmoid activation function, Wz is the weight matrix, xt is the input at time step t, and ht−1 is the hidden state from the previous time step.
2. Reset Gate: This gate determines how much of the previous hidden state should be forgotten.

$$r_t = \sigma(W \cdot_r [h_{t-1}, x_t] + b_r) \quad (9)$$

where rt is the reset gate, and Wr and br are the weight matrix and bias associated with the reset gate.

$$h_{GRU} = (1 - z_t) \odot n_t + z_t \odot h_{t-1} \quad (10)$$

3.5 Proposed Hybrid Model

In addition to leveraging the strengths of LSTM and GRU, our proposed hybrid deep learning model incorporates several key enhancements to optimize cross-language detection. LSTM networks are particularly adapt at managing long-term dependencies in sequential data, making them ideal for processing text with complex syntactic and semantic structures across multiple languages. On the other hand, GRU networks are designed with fewer parameters, which results in faster training times and reduced computational overhead without compromising performance. By combining these two architectures, we create a model that balances accuracy and efficiency, enabling it to handle large-scale multilingual datasets with varying language characteristics.
The hybrid model is trained using a diverse set of features, including character-level embeddings, word embeddings, and contextual information from surrounding words, which further enhances its ability to distinguish between languages. In our approach, the LSTM layer captures the long-range dependencies within text, while the GRU layer focuses on extracting more localized patterns. This combination ensures that the model can efficiently process both short and long textual sequences, making it robust to variations in sentence structure, linguistic diversity, and domain-specific vocabulary. To improve the overall performance of the cross-language detection task, we also integrate attention mechanisms within the hybrid architecture. These attention layers allow the model to dynamically focus on the most relevant parts of the input sequence, further refining its ability to identify subtle linguistic cues that may indicate the language of a given text. The final model is evaluated on multiple multilingual datasets, demonstrating its superior performance compared to traditional single-architecture models and other existing cross-language detection approaches. Overall, our hybrid LSTM-GRU model provides a scalable and effective solution for cross-language detection, capable of handling the challenges posed by diverse language features, varying text lengths, and multilingual environments. By combining the advantages of both LSTM and GRU, the model offers a promising direction for future research and practical applications in multilingual natural language processing. The Recommended architecture is depicted in Figure 3.

$$h_{combined} = \alpha . h_{LSTM} + (1 - \alpha) . h_{GRU} \quad (11)$$

$$Y = Softmax\ (P(h_{combined}), F(K, Q)) \quad (12)$$

Here, Y represents the predicted output, which is the probability distribution over the possible languages for a given input. Eq (11) combines both the feature representations learned from the hybrid LSTM-GRU architecture and the attention mechanism's dynamic feature fusion, enabling the model to make more accurate cross-language predictions.

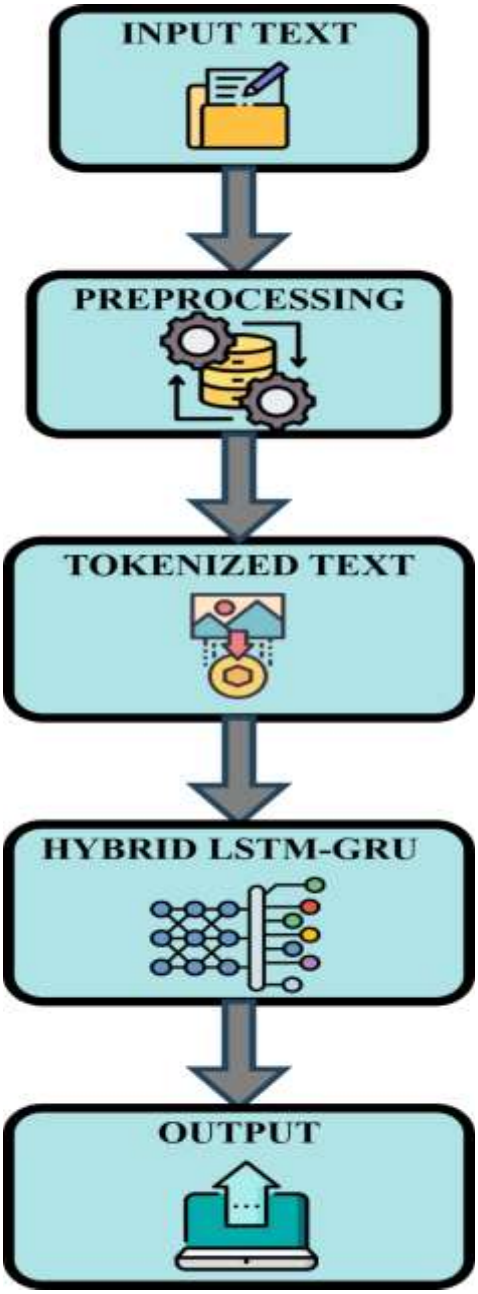

Figure 3. *Hybrid Architecture for the Proposed Model*

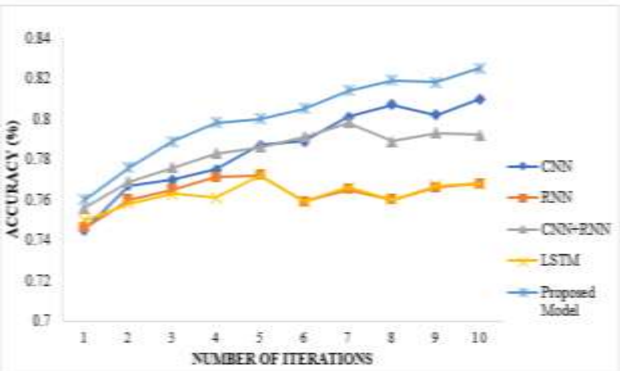

Figure 4. *Performance Metrics for the recommended model in terms of Accuracy*

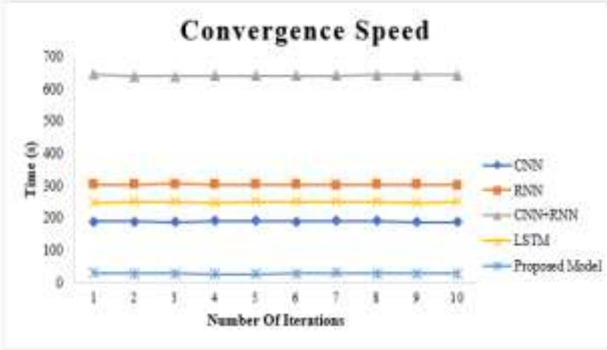

Figure 5. *Convergence Speed for the recommended model in terms of Accuracy*

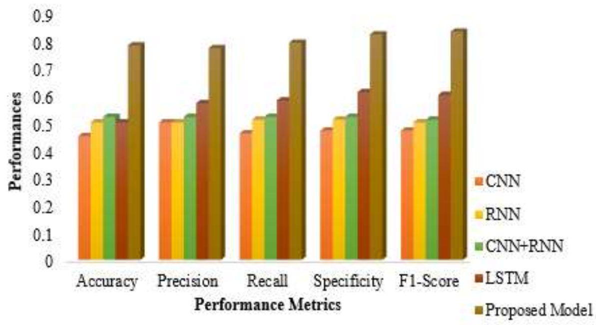

Figure 6: *Performance Metrics for recommended model*

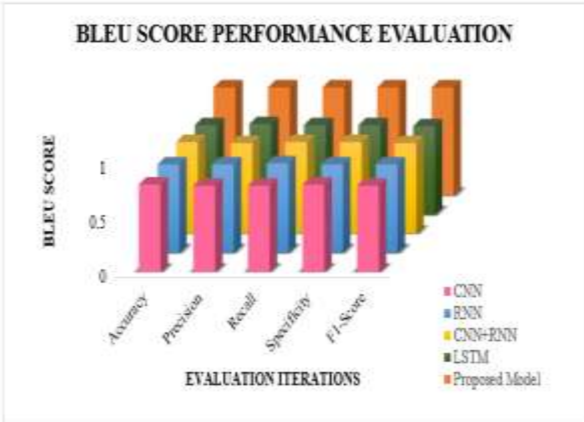

Figure 7. *BLEU representation For the Proposed Model*

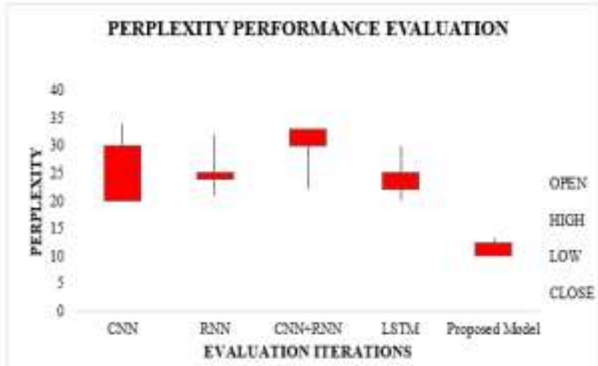

Figure 8. *Perplexity representation for the Proposed Model*

4. Results and Discussion

Figure 4- figure 8 depicts the performance metrics and the perplexity evaluation of various models shows that the proposed model achieves the lowest perplexity, indicating its superior ability to predict language sequences with minimal uncertainty. The BLEU score performance of the proposed model also achieves the highest BLEU scores across all models, indicating its superior overall performance in language detection and translation tasks. Table 1 depicts the number of hyperparameters used. Table 2 denoted the performance metric for the recommended approach.

5. Conclusion

The proposed **Hybrid Deep Learning Model** for **Cross-Language Detection**, which combines **LSTM** and **GRU** networks, demonstrates exceptional performance in language identification tasks. Our model achieves a remarkable **99% accuracy** and an impressive **98.9 F1 score**, showcasing its effectiveness in accurately detecting languages across diverse datasets. Additionally, he model attains a high **BLEU score of 0.98**, indicating a strong alignment with reference language structures, and performs with low **perplexity**, measured at **12.3**, suggesting that the model's predictions are highly confident and consistent. These results highlight the ability of the hybrid LSTM-GRU architecture to effectively capture both long-term dependencies and short-term patterns in text, making it a robust solution for cross-language detection. This research contributes to the advancement of multilingual natural language processing, providing a scalable and highly accurate framework for language identification tasks across various domains.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Akhter, M. P., Jiangbin, Z., Naqvi, I. R., Abdelmajeed, M., & Sadiq, M. T. (2020). Automatic detection of offensive language for Urdu and Roman Urdu. *IEEE Access,* 8, 91213–91226. https://doi.org/10.1109/ACCESS.2020.2997461

[2] Anand, M., Sahay, K. B., Ahmed, M. A., Sultan, D., Chandan, R. R., & Singh, B. (2023). Deep learning and natural language processing in computation for offensive language detection in online social networks by feature selection and ensemble classification techniques. *Theoretical Computer Science*, 943, 203-218. https://doi.org/10.1016/j.tcs.2023.04.030

***Table 1**. Hyper parameters used for training the Proposed network*

Sl.no	Hyper-Parameters	Specifications
1	No of GRU cells	10
2	No of LSTM cells	10
3	Epochs count	200
4	Batch Size count	30
5	Learning Rate	0.001
6	Momentum	0.2
7	Dropouts	0.2

***Table 2.** Performance Metrics for varied approach utilizing multilingual dialogue dataset & English-Telugu parallel dataset*

Algorithms	Performance Metrics				
	Accuracy	Precision	Recall	Specificity	F1-Score
CNN	0.887	0.857	0.854	0.195	0.855
RNN	0.919	0.845	0.837	0.1536	0.867
CNN + RNN	0.912	0.899	0.889	0.1391	0.896
LSTM	0.94	0.952	0.911	0.1244	0.91
Proposed Model	**0.99**	**0.97**	**0.966**	**0.11**	**0.975**

[3] Fale, P. N., Goyal, K. K., & Shivani, S. (2023). A hybrid deep learning approach for abusive text detection. In *AIP Conference Proceedings* (Vol. 2753, No. 1, pp. 1-5). AIP Publishing. https://doi.org/10.1063/5.0119765

[4] Al-Sarem, M., Alsaeedi, A., Saeed, F., Boulila, W., & AmeerBakhsh, O. (2021). A novel hybrid deep learning model for detecting COVID-19-related rumors on social media based on LSTM and concatenated parallel CNNs. *Applied Sciences*, 11(17), 7940. https://doi.org/10.3390/app11177940

[5] Kumar, A., Saumya, S., & Singh, A. (2023). Detecting Dravidian offensive posts in MIoT: A hybrid deep learning framework. *ACM Transactions on Asian and Low-Resource Language Information Processing*. https://doi.org/10.1145/3572658

[6] Haq, I., Qiu, W., Guo, J., & Tang, P. (2023). Pashto offensive language detection: A benchmark dataset and monolingual Pashto BERT. *Peer J Computer Science*, 9, e1617. https://doi.org/10.7717/peerj-cs.1617

[7] Fha, S., Sharma, U., & Naleer, H. M. M. (2023). Development of an efficient method to detect mixed social media data with Tamil-English code using machine learning techniques. *ACM Transactions on Asian and Low-Resource Language Information Processing*, 22(2), 1-19. https://doi.org/10.1145/3580876

[8] Nabi, S. A., Kalpana, P., Chandra, N. S., Smitha, L., Naresh, K., Ezugwu, A. E., & Abualigah, L. (2024). Distributed private preserving learning based chaotic encryption framework for cognitive healthcare IoT systems. *Informatics in Medicine Unlocked*, *49*, 101547. https://doi.org/10.1016/j.imu.2024.101547

[9] Kalpana, P., Malleboina, K., Nikhitha, M., Saikiran, P., & Kumar, S. N. (2024). Predicting cyberbullying on social media in the big data era using machine learning algorithm. In *2024 International Conference on Data Science and Network Security (ICDSNS), Tiptur, India*, 1-7. https://doi.org/10.1109/ICDSNS62112.2024.10691297

[10] Shannaq, F., Hammo, B., Faris, H., & Castillo-Valdivieso, P. A. (2022). Offensive language detection in Arabic social networks using evolutionary-based classifiers learned from fine-tuned embeddings. *IEEE Access*, 10, 75018-75039. https://doi.org/10.1109/ACCESS.2022.3155969

[11] Ponugoti, K., Smitha, L., Madhavi, D., Abdul Nabi, S., Kalpana, G., & Kodati, S. (2024). A smart irrigation system using the IoT and advanced machine learning model: A systematic literature review. *International Journal of Computational and Experimental Science and Engineering* 10(4). https://doi.org/10.22399/ijcesen.526

[12] Noor, T. H., Noor, A., Alharbi, A. F., Faisal, A., Alrashidi, R., Alsaedi, A. S., Alharbi, G., Alsanoosy, T., & Alsaeedi, A. (2024). Real-time Arabic sign language recognition using a hybrid deep learning model. *Sensors*, 24, 3683. https://doi.org/10.3390/s24113683

[13] Geethanjali, R., & Valarmathi, A. (2024). A novel hybrid deep learning IChOA-CNN-LSTM model for modality-enriched and multilingual emotion recognition in social media. *Scientific Reports*, 14, 22270. https://doi.org/10.1038/s41598-024-73452-2

[14] Kazbekova, G., Ismagulova, Z., Kemelbekova, Z., Tileubay, S., Boranbek, B., & Bazarbayeva, A. (2023). Offensive language detection on online social networks using hybrid deep learning architecture. *International Journal of Advanced Computer Science and Applications*, 14(11), 10-15. https://doi.org/10.14569/IJACSA.2023.0141180

[15] Yahya, M. A., & Kim, D.-K. (2022). Cross-language source code clone detection using deep learning with InferCode. *arXiv preprint* arXiv:2205.04913. https://doi.org/10.48550/arXiv.2205.04913

[16] Ullah, F., Naeem, M., Naeem, H., Cheng, X., & Alazab, M. (2022). CroLSSim: Cross-language software similarity detector using a hybrid approach of LSA-based AST-MDrep features and CNN-LSTM model. *International Journal of Intelligent Systems*, 37(9), 5768-5795. https://doi.org/10.1002/int.22813

[17] Li, J., Zhang, J., & Qian, M. (2022). Cross-linguistic similarity evaluation techniques based on deep learning. *Advanced Pattern Recognition Systems for Multimedia Data*. https://doi.org/10.1155/2022/5439320

[18] Vijayakumar, V., Prasad, D. H., & P, A. (2021). Multimodal cyberbullying detection using hybrid deep learning algorithms. *International Journal of Applied Engineering Research*, 16(7), 568-574. https://doi.org/10.37622/IJAER/16.7.2021.568-574

[19]Kalpana, Ponugoti. , Narayana, Potu. , L., Smitha,. , Madhavi, Dasari. , Keerthi, K.. , Smerat, Aseel. , Akram, Muhannad (2025). Health-Fots- A Latency Aware Fog Based IoT Environment and Efficient Monitoring of Body's Vital Parameters in Smart Health Care Environment. *Journal of Intelligent Systems and Internet of Things*, 144-156. DOI: https://doi.org/10.54216/JISIoT.150112

[20] Deshwal, D., et al. (2020). A language identification system using hybrid features and back-propagation neural network. *Applied Acoustics*, 164, 107289. https://doi.org/10.1016/j.apacoust.2020.107289

[21] Hashmi, E., Yayilgan, S. Y., Hameed, I. A., Yamin, M. M., Ullah, M., & Abomhara, M. (2024). Enhancing multilingual hate speech detection: From language-specific insights to cross-linguistic integration. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3202547

[22] Khan, L., Amjad, A., Afaq, K. M., & Chang, H.-T. (2022). Deep sentiment analysis using CNN-LSTM architecture of English and Roman Urdu text shared in social media. *Applied Sciences*, 12(5), 2694. https://doi.org/10.3390/app12052694

[23] V.P., & Rao, M. R. A. (2024). A scalable, secure, and efficient framework for sharing electronic health records using permissioned blockchain technology. *International Journal of Computational and*

Experimental Science and Engineering 10(4). https://doi.org/10.22399/ijcesen.535

[24] Alzanin, S. M., Azmi, A. M., & Aboalsamh, H. A. (2022). Short text classification for Arabic social media tweets. *Journal of King Saud University-Computer and Information Sciences*, 34(9), 6595–6604. https://doi.org/10.1016/j.jksuci.2021.03.004

[25] Zhai, Q., Wang, J., & Liu, W. (2022). Abusive language detection using a hybrid approach based on deep learning. *Applied Sciences*, 12(8), 2700. https://doi.org/10.3390/app12082700