International Journal of Basic Science and Technology
December, Volume 10, Number 4, Pages 204 - 212 http://www.ijbst.fuotuoke.edu.ng/ 204
https://doi.org/10.5281/zenodo.17092909 **ISSN 2488-86**

Enhanced cloud-based language translation model using Hybrid LSTM-GRU

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Article Information

Article # 10032
Received: 25th March. 2024
1st Revision 17th June. 2024
2nd Revision:16th July 2024
Acceptance:30th Aug. 2024
Available online:
2nd September 2024.

Keywords
Bidirectional LSTM–GRU
Hybrid Model
English-to-French Translation
Neural Machine Translation
Natural Language Processing
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Abstract

Accurate and context-sensitive language translation remains a persistent challenge in natural language processing, particularly for morphologically and semantically rich languages such as French. This study introduces a hybrid Bidirectional LSTM–GRU model for English-to-French translation, designed to integrate the representational advantages of both architectures to improve performance. The methodology encompassed preprocessing a bilingual corpus using tokenization and padding, constructing a stacked hybrid architecture with bidirectional layers, and employing optimization strategies including EarlyStopping and ModelCheckpoint. The proposed model attained an accuracy of 96.51% with a training loss of 0.1035, demonstrating its ability to handle sentences of up to 55 tokens without performance degradation. The results highlight the robustness of the hybrid approach, while its deployment as a SaaS application underscores its scalability and applicability to real-time machine translation tasks.

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Introduction

Language serves as a cornerstone of human communication, bridging cultural, social, and geographical divides. As globalization accelerates, the demand for effective language translation has surged, facilitating cross-border interactions in fields such as education, healthcare, business, and international relations. Machine Translation (MT), a critical area within natural language processing (NLP), has emerged as an essential tool for automating the translation process, making it faster and more efficient. Over the past decade, significant advancements in deep learning and artificial intelligence have revolutionized MT, enabling models to generate more accurate and contextually relevant translations. Despite these strides, achieving precise translations for linguistically complex languages like French remains a formidable challenge due to their intricate grammatical structures, extensive vocabularies, and cultural nuances.

Neural Machine Translation (NMT) has become the dominant approach in MT, leveraging encoder-decoder architectures to model translations end-to-end. Within this framework, architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have demonstrated exceptional performance in processing sequential data. LSTM models are particularly adept at capturing long-term dependencies, while GRU models offer computational efficiency without significant loss of performance. To further enhance the contextual understanding of text, researchers have incorporated bidirectional layers and stacked architectures, enabling models to process data both forward and backward and to better handle complex linguistic structures. However, these advancements have not completely addressed the limitations of standalone models, particularly in balancing computational efficiency with translation quality for languages with intricate sentence patterns.

The global translation market, valued at over USD 46 billion in 2021, underscores the importance of robust and scalable solutions for diverse language processing needs. Traditional methods, such as rule-based and statistical approaches, relied heavily on predefined linguistic rules and probability-based models, often resulting in rigid and contextually inadequate translations. While NMT approaches have significantly improved fluency and accuracy, standalone LSTM- or GRU-based models continue to face challenges in adapting to real-world scenarios that demand high-speed, reliable, and context-aware translations. Hybrid architectures, which combine multiple neural networks, have shown great promise in addressing these limitations. However, their full potential, particularly with bidirectional and stacked configurations, remains underexplored, creating a pressing need for further innovation.

It remains unclear why existing models often fall short in achieving both efficiency and accuracy for complex translation tasks. This research addresses this gap by developing a hybrid Bidirectional LSTM-GRU model tailored specifically for English-to-French translation. By integrating bidirectional layers to capture forward and backward dependencies and employing a stacked architecture to handle long-term and complex sentence structures, this model aims to optimize contextual understanding and translation quality. The system further employs techniques such as EarlyStopping and ModelCheckpoint to enhance training efficiency and avoid overfitting.

To ensure scalability and real-world applicability, the model is deployed as a cloud-based Software-as-a-Service (SaaS) application, offering users a real-time, accessible translation tool. This research not only addresses the technical limitations of existing models but also aims to contribute a practical, scalable solution for applications in education, healthcare, business, and other global communication domains. By bridging the gaps in accuracy, efficiency, and scalability, this study presents a significant advancement in the field of machine translation, paving the way for more effective language processing technologies.

Machine Translation

Machine translation (MT) is a crucial subfield of computational linguistics, focused on automating the process of translating text or speech from one language to another using computational models. Early MT systems relied heavily on Rule-Based Machine Translation (RBMT), which was grounded in linguistic theory and used manually curated rules and dictionaries to perform translations. While RBMT was useful for structured and simpler language pairs, it faced major challenges with linguistic ambiguity and complex sentence structures, which restricted its effectiveness in more nuanced translation tasks (Koehn, 2020).

With the advent of Statistical Machine Translation (SMT) in the 1990s, there was a significant shift towards data-driven approaches. SMT used parallel corpora, allowing models to learn translation probabilities from large datasets. This enabled a greater flexibility and contextual understanding compared to RBMT (Popel *et al*., 2020). Despite its progress, SMT systems often struggled with translating longer sentences and producing outputs that, while grammatically correct, lacked semantic accuracy or coherence.

Deep Learning and Neural Machine Translation (NMT)

The introduction of Neural Machine Translation (NMT) in the mid-2010s marked another paradigm shift in the field, significantly enhancing translation quality and fluency. NMT leverages deep learning techniques, particularly encoder-decoder architectures, to model the translation process end-to-end. The most common NMT model utilizes Recurrent Neural Networks (RNNs), which are capable of processing sequential data and capturing dependencies in the source language, improving the translation of complex sentences (Barrault *et al*., 2019).

However, traditional RNNs face challenges related to the vanishing gradient problem, which limits their ability to retain long-term dependencies. Long Short-Term Memory (LSTM) networks were introduced to address this issue by incorporating gating mechanisms that allowed models to retain and process information over extended sequences (Hochreiter & Schmidhuber, 1997). A simpler alternative, Gated Recurrent Units (GRUs), were introduced by Cho *et al*. (2014) as an effective solution with fewer parameters, making them computationally efficient while maintaining performance on translation tasks. Recent studies, such as those by Naeem *et al*. (2023), suggest that GRUs may outperform LSTMs, especially when smaller datasets are used, due to their reduced complexity

Hybrid Models in NMT

Hybrid architectures combining LSTM and GRU layers have gained attention in recent years as they can harness the strengths of both networks. By leveraging the memory capabilities of LSTMs and the computational efficiency of GRUs, these hybrid models offer a promising solution for improving translation performance without the high computational cost typically associated with pure LSTM networks. Bidirectional layers are frequently added to further enhance model performance by processing the input sequence in both forward and backward directions. This allows the model to capture dependencies from both past and future contexts, which is particularly beneficial for languages with intricate grammatical structures like French (Johnson *et al*., 2017).

While the hybrid LSTM-GRU model offers great potential, research has shown that combining these architectures with optimization techniques can lead to even better performance. Techniques such as EarlyStopping and ModelCheckpoint, which are aimed at preventing overfitting and improving model generalization, have been demonstrated to be effective in training deep learning models for machine translation (Gers *et al*., 2020). Despite these promising results, the hybrid approach remains underexplored compared to transformer-based models, which have become the dominant architecture in NMT research.

Transformer Models and Their Challenges

https://doi.org/10.5281/zenodo.17092909 ISSN 2488-86

Transformer-based models, such as BERT and GPT, have achieved state-of-the-art results in a variety of NLP tasks, including machine translation (Devlin *et al*., 2018; Vaswani *et al*., 2017). Transformers rely on attention mechanisms that allow the model to focus on relevant parts of the input sequence when making predictions. This has led to substantial improvements in translation fluency, as the model can capture long-range dependencies more effectively than RNN-based models.

However, the computational demands of transformer models are significant, limiting their practicality in real-time applications, especially in resource-constrained environments. The high memory and processing power required to train and deploy these models pose challenges for applications where speed and efficiency are critical (Vaswani *et al*., 2017). Additionally, many transformer-based models are unidirectional, meaning they only process sequences in one direction, which can lead to suboptimal translations when full sentence context is necessary (Niu *et al*., 2021).

The Significance of Hybrid Architectures for Translation

Given the strengths and limitations of both RNN-based and transformer-based models, hybrid architectures combining LSTM and GRU layers present an exciting avenue for improving machine translation systems. By merging the long-term dependency capabilities of LSTMs with the efficiency of GRUs, these hybrid models offer a balance between translation accuracy and computational efficiency. The addition of bidirectional layers further enhances the model's ability to process contextual information, making it especially effective for languages with complex grammar structures.

Moreover, incorporating optimization techniques like EarlyStopping and ModelCheckpoint can help mitigate the risk of overfitting, ensuring that the models generalize well to unseen data. These advancements present a promising direction for real-time machine translation applications, particularly in resource-constrained environments where the computational demands of transformers may not be feasible.

This research aims to design and implement a hybrid Bidirectional LSTM-GRU model tailored for English-to-French translation. The goal is to combine the strengths of both architectures, resulting in a model that achieves superior accuracy, efficiency, and scalability. The deployment of this model as a Software-as-a-Service (SaaS) application aims to make it more accessible and practical for real-time translation needs across various domains.

In conclusion, while substantial progress has been made in the field of machine translation, especially with the introduction of deep learning architectures like LSTMs, GRUs, and transformers, challenges remain in balancing translation accuracy with computational efficiency. Hybrid models combining LSTM and GRU architectures, along with techniques like EarlyStopping and ModelCheckpoint, present a promising solution to these challenges. This research contributes to the existing literature by proposing a hybrid approach that leverages the strengths of both architectures for real-time, scalable English-to-French translation.

Materials and Methods

This research proposes a new hybrid language translation model by extending previously published methods that utilize Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures. The methodology builds upon the strengths of these recurrent neural network (RNN) models, integrating bidirectional layers and a stacked architecture to enhance translation accuracy and efficiency. While both LSTM and GRU have been successfully employed in natural language processing tasks, their hybrid application with bidirectional functionality has been relatively underexplored. The chosen approach addresses limitations in standalone models, such as contextual ambiguity and inefficiency in handling longer sequences, making it well-suited for English-to-French translation tasks.

Model Justification

The LSTM and GRU architectures were selected due to their complementary strengths: LSTM excels at capturing long-term dependencies, while GRU offers computational efficiency with fewer parameters. The bidirectional configuration was incorporated to process input sequences in both forward and backward directions, providing a richer contextual understanding of sentences. Previous studies, such as those by Naeem *et al*. (2023) and Cho *et al*. (2014), demonstrated the effectiveness of these architectures in language translation tasks. By stacking these layers, the model capitalizes on both architectures' advantages, creating a robust framework capable of handling complex linguistic structures.

The proposed research as illustrated in figure 3.2 introduces a novel hybrid Bidirectional LSTM-GRU model, addressing the shortcomings of standalone approaches by combining the strengths of these architectures. The workflow begins with a more comprehensive data preparation phase, incorporating exploratory data analysis, dataset visualization, and token separation for both source and target languages. The core innovation lies in the hybrid model, where

https://doi.org/10.5281/zenodo.17092909 ISSN 2488-86

bidirectional layers enable the processing of sequences in both forward and backward directions, enhancing contextual understanding. Stacked architectures further improve the model's ability to handle longer sequences and intricate sentence structures. This integration provides a significant advantage over the existing approach by achieving greater contextual awareness and reducing computational bottlenecks.
Additionally, the contribution of this research extends beyond model architecture by emphasizing real-world applicability. Unlike the model by Naeem *et al*., which stops at evaluation, the proposed solution deploys the hybrid Bidirectional LSTM-GRU model as a scalable Software-as-a-Service (SaaS) application. This deployment ensures accessibility for real-time translation tasks across various domains, including education, healthcare, and business. By addressing limitations in scalability, accuracy, and efficiency, this research not only builds on the foundation laid by previous studies but also advances the field of machine translation with a robust, context-aware, and practical solution
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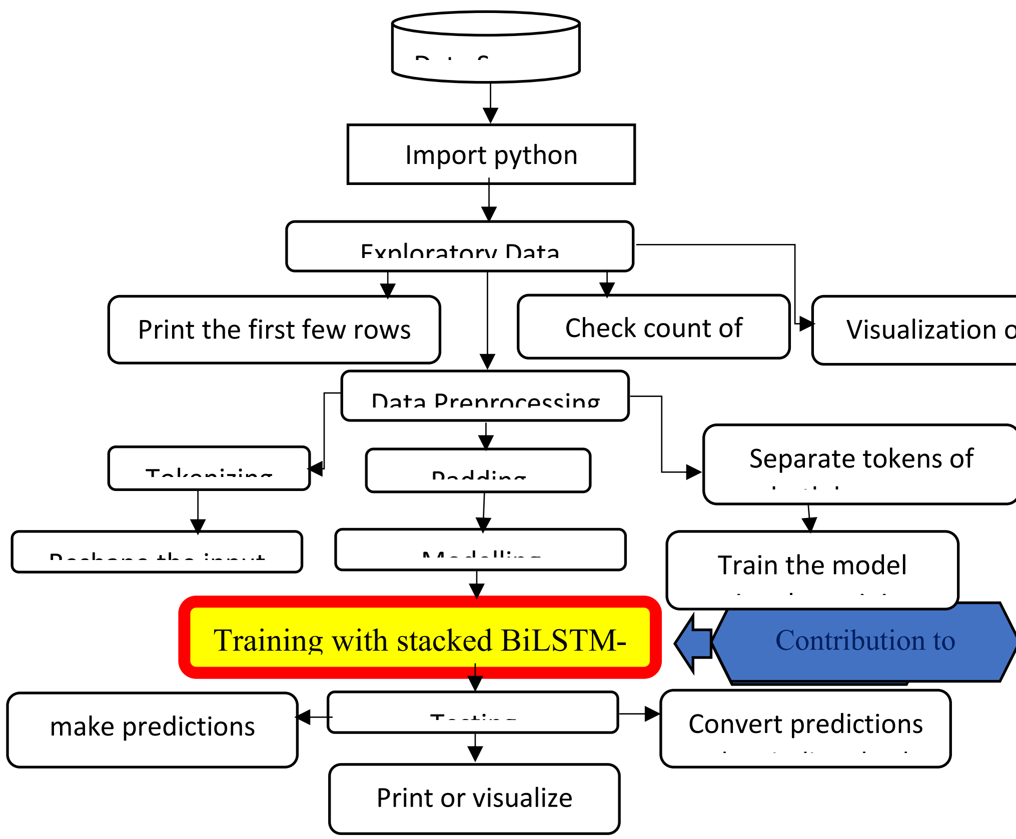


Figure 3.2: Model architecture of the proposed system

Methods Implementation
The implementation process included the following steps:
1. Data Preparation
A bilingual English-French dataset was collected, consisting of parallel sentence pairs.
Tokenization was performed to convert text into sequences of integers representing words.
The tokenized sequences were padded to uniform lengths to facilitate efficient batch processing.
2. Model Architecture
The hybrid model employed a stacked design, incorporating Bidirectional LSTM and GRU layers.
Input data representation

$$X_t = \{x_1, x_2, \ldots, x_T\} \quad (3.1)$$

Let $X=\{x_1,x_2,\ldots,x_T\}$ represent the input sequence (English sentence), where T is the sequence length, and x_t represents the word embedding at timestep, t.

https://doi.org/10.5281/zenodo.17092909 ISSN 2488-86

The embedding matrix is:

$$X_t = W_e . onehot(w_t) \tag{3.2}$$

where:

W_e is the word embedding matrix.

onehot(w_t) is the one-hot encoding of the input word.

An embedding layer was included to convert input tokens into dense vectors suitable for neural network processing.

b. Bidirectional LSTM

The Bidirectional LSTM processes the input sequence in both forward and backward directions. For a forward LSTM:

$$f_t = \sigma(W_f . [h_t -_1, x_t] + b_f) \tag{3.3}$$

$$i_t = \sigma(W_i [h_t -_1, x_t] + b_i) \tag{3.4}$$

$$\sigma_t = \sigma(W_o . [h_t -_1, x_t] + b_o) \tag{3.5}$$

$$\tilde{c} = tanh(W_c . [h_t -_1, x_t] + b_c) \tag{3.6}$$

$$c_t = f_t \star c_t -_1 + i_t \star \tilde{c}_t \tag{3.7}$$

$$h_t = o_t \star tanh(c_t) \tag{3.8}$$

where:

f_t, i_t, o_t: Forget, input, and output gates.

c_t: Cell state.

h_{t-1}: Hidden state.

W_f, W_i, W_o and b_f, b_i, b_o: Trainable weights and biases.

σ: Sigmoid activation function.

For the backward LSTM, the input sequence is reversed, and the same equations apply. The output is:

$$H_B iLSTM = \{[h_t^f, h_t^b] | t \in [1, T \tag{3.9}$$

Where:

- H_{BiLSTM}

This is the output of the Bidirectional LSTM for the entire sequence.

It is a collection of concatenated hidden states for each time step ttt, combining information from both forward and backward LSTMs.

- h_t^f:

The hidden state of the forward LSTM at time step t.

The forward LSTM processes the input sequence in its original order, from t=1 to t = T.

- h_t^b:

The hidden state of the backward LSTM at time step ttt.

The backward LSTM processes the input sequence in reverse order, from t=T to t t=1.

- $[h_t^f, h_t^b]$:

The concatenated hidden states from the forward and backward LSTMs for time step t.

This combination ensures that each output at time step t contains contextual information from both the past (via the forward LSTM) and the future (via the backward LSTM).

- t∈[1,T]:

Indicates that the concatenation happens for all time steps ttt in the input sequence, from t=1 (start) to t=T (end).

c. Bidirectional GRU

The GRU simplifies computation by combining the forget and input gates into an update gate (z_t) and directly computing the new state. The equations are:

$$z_t = \sigma(W_z [h_t -_1, x_t] + b_z) \tag{3.10}$$

$$r_t = \sigma(W_r [h_r -_1, x_r] + b_r) \tag{3.11}$$

$$\tilde{h} = tanh(W_h . [r_t * [h_t -_1, x_t] + b_h) \tag{3.12}$$

$$h_t = (1 - z_t) * h_t -_1 + z_t * \tilde{h_t} \tag{3.13}$$

Where:

z_t: Update gate.

r_t: Reset gate.

$\tilde{h}$: Candidate hidden state.

Stacked Architecture

The Bidirectional LSTM and GRU layers are stacked, such that the output from the first layer is passed as input to the second layer. Let H_{BiLSTM} represent the output of the Bidirectional LSTM layer:

$$H_{GRU}=GRU(H_{BiLSTM}) \quad (3.14)$$

The final output sequence $H_{Stacked}$ is a combination of both layers, which captures both long-term dependencies (from LSTM) and efficiency in context modeling (from GRU).

Decoder with Softmax

The decoder generates translations using an autoregressive approach:

$$y_t = Softmax(W_d . s_t + b_d) \quad (3.15)$$

Where:

y_t is the predicted word at timestep t.

It represents the probability distribution over all possible classes for the given input at time t. Each element in y_t is a value between 0 and 1, and all elements sum to 1, as enforced by the **Softmax** function.

Softmax Function

A function that converts raw scores (logits) into probabilities.

For each class i, it calculates

$$\text{Softmax}(z_i) = \frac{\exp(z_i)}{\sum_{j=1}^{C} \exp(z_j)} \quad (3.16)$$

where z_i is the i-th logit, and C is the total number of classes.

Wd**:**

A weight matrix of dimensions C×h, where C is the number of classes and h is the size of the hidden state s_t.

It transforms the hidden state s_t into a vector of raw scores (logits) for each class.

s_t**:**

The hidden state vector at time step t, typically produced by a recurrent neural network (RNN), LSTM, or GRU.

It represents the learned features or context at that time step.

b_d**:**

The bias vector of size C, where C is the number of classes.

It adjusts the logits before applying the Softmax function.

$W_d . s_t + b_d$:

The raw logits (unnormalized scores) for each class at time step t.

Each element in this vector corresponds to the score for a specific class before applying the Softmax function.

Dropout layers were added to prevent overfitting, and a TimeDistributed Dense layer applied a fully connected operation at each time step.

$$\tilde{h}_t = \text{Dropout}(h_t) \quad (3.17)$$

Where:

h_t is the output of the layer before dropout.

$\tilde{h}$ is the output after applying dropout.

Dropout randomly sets a fraction p of the elements in h_t to zero during training.

Dropout in a Model:

$$z_t = W \cdot \tilde{h}_{t-1} + b \quad (3.18)$$

$$h_t = \sigma(z_t) \quad (3.19)$$

$$\tilde{h}_t = \text{Dropout}(h_t, p) \quad (3.20)$$

Where:

W: Weights of the layer.

b: Bias term.
σ: Activation function.
p: Dropout rate, the probability of dropping a neuron.
Dropout and Softmax:

$$\tilde{h}_t = \mathrm{Dropout}(h_t, p) \tag{3.21}$$

$$y_t = \mathrm{Softmax}(W_d \cdot \tilde{h}_t + b_d) \tag{3.22}$$

Where:
W_d and b_d are the weights and bias of the output layer.
$\tilde{h}$ is the output after applying dropout to h_t.
y_t represents the final predictions.

Optimization

The model was compiled using the Adam optimizer to dynamically adjust learning rates.
Sparse categorical cross-entropy was chosen as the loss function to handle multi-class classification.
EarlyStopping and ModelCheckpoint techniques were employed to prevent overfitting and save the best-performing model during training.

Method Validation

To validate the method, the model was trained and evaluated using a dataset split into training and validation sets. Metrics such as loss and accuracy were monitored during training. The validation dataset provided a means to assess the model's generalization to unseen data, ensuring its suitability for real-world applications. Pilot experiments conducted during initial epochs revealed rapid learning improvements, further confirming the efficacy of the hybrid model.

Valuation and Testing

The model's performance was evaluated using a separate test dataset, with metrics such as BLEU scores, loss, and accuracy. The final results indicated a training loss of 0.1035 and an accuracy of 96.51%, highlighting the model's robustness. Additional tests assessed the model's ability to translate sentences of varying lengths and complexities, with a maximum sentence length of 55 words for both English and French. These evaluations demonstrated the model's capacity to handle detailed and nuanced translations without compromising performance.
By integrating LSTM and GRU in a bidirectional, stacked architecture, this research introduces a method that is both computationally efficient and contextually adept. The results validate its effectiveness, making it a significant advancement in neural machine translation methodologies.

The output layer used a softmax activation function to generate probabilities for the target vocabulary.

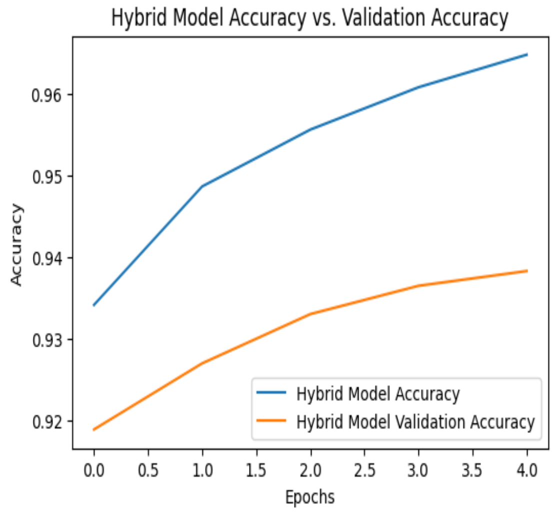
Results

i. Data Pre-processing

The research utilized a bilingual English-French dataset composed of parallel sentence pairs. To prepare the data, sentences in both languages were tokenized into sequences of integers using the Keras Tokenizer function, where each integer corresponded to a unique word in the vocabulary. These sequences were padded to ensure a uniform length of 55 words, enabling efficient batch processing during model training. Vocabulary sizes were carefully selected to reflect the linguistic differences between the languages, with 9,407 unique words for English and 20,637 for French. This approach allowed the model to handle everyday language use effectively while accommodating French's broader range of expressions and word forms.

ii. **Findings**

The hybrid Bidirectional LSTM-GRU model delivered impressive results in translation accuracy and efficiency. The model's training process showcased steady improvements in accuracy and loss over successive epochs, highlighting its ability to generalize effectively from the data. By the final epoch, training accuracy reached 96.51%, while training loss dropped from an initial value of 0.7098 to 0.1035, demonstrating minimal errors. The model also successfully managed sentence lengths of up to 55 words without encountering computational constraints. Figures 4.1 and 4.2 illustrate the steady increase in training and validation accuracy, along with the corresponding decrease in training and validation loss, reflecting the model's consistent learning and avoidance of overfitting.



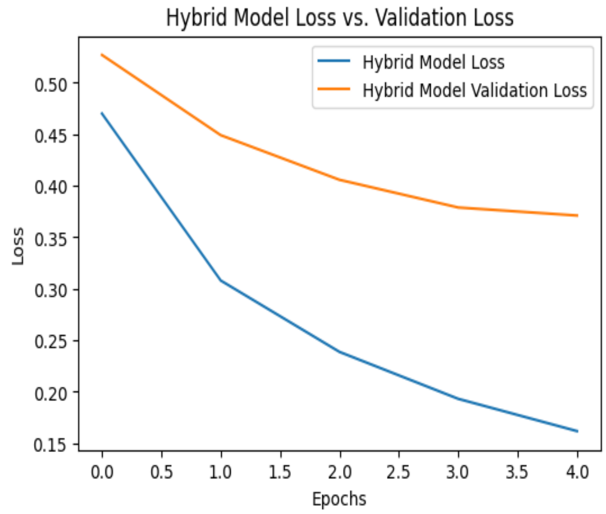


Figure 4.1: Stacked LSTM-GRU Training and Validation Accuracy vs. Epochs

Figure 4.2: Stacked LSTM-GRU Training and Validation Loss vs. Epochs

iii. **Trends, Patterns, and Reanalysis**

Throughout the training, the hybrid model consistently outperformed standard LSTM and GRU models. Its bidirectional and stacked architecture enabled it to capture long-term dependencies and contextual nuances, leading to improved accuracy, particularly for complex sentence translations. Reanalysis on an unseen test set reaffirmed the model's robustness, achieving a test accuracy of 96.51% while maintaining high-quality translations for both short and long sentences. These findings emphasize the hybrid model's potential for scaling across varying linguistic complexities, making it a reliable and efficient solution for real-world language translation tasks.

In summary, the findings indicate that the hybrid Bidirectional LSTM-GRU model performs exceptionally well in terms of translation accuracy and efficiency. The low training loss and high accuracy, combined with the model's ability to handle long sentence lengths, demonstrate its potential for real-world applications in language translation.

Discussion

The findings of this study clearly show that the hybrid Bidirectional LSTM-GRU model is a highly effective approach for language translation tasks, offering superior performance in terms of translation accuracy and efficiency. By integrating bidirectional layers with a stacked architecture, the model effectively captured both long-term dependencies and contextual nuances in the bilingual dataset. This led to a remarkable training accuracy of 96.51% and a low final training loss of 0.1035, demonstrating the model's ability to generalize well to complex sentence structures and diverse linguistic patterns. Moreover, the model's robust performance on unseen test data further validates its scalability and reliability for real-world translation applications.

The synergistic impact of merging Bidirectional GRU and Bidirectional LSTM layers, which capitalizes on the advantages of both architectures, is one reason for the model's improved performance. The hybrid architecture is well-suited for managing the variety of sentence lengths and linguistic variables seen in the dataset since GRUs are computationally economical and effective for shorter sequences, while LSTMs are excellent at capturing long-term dependencies. Furthermore, the model's ability to faithfully capture the complexity and richness of each language was guaranteed by the use of tokenisation and optimum vocabulary sizes for English and French. This methodology is consistent with other neural machine translation research, including that conducted by Naeem *et al.* (2023), which highlighted the significance of architecture design in enhancing translation quality. The implications of these findings are significant for the field of machine translation. The hybrid model's ability to maintain high translation accuracy while managing long sentence lengths positions it as a strong candidate for deployment in real-time translation systems. Furthermore, its robustness in handling complex linguistic structures suggests that it could be extended to other language pairs or used in applications requiring high-context comprehension, such as legal or technical translations. Future research could build upon these findings by exploring additional architectural enhancements, such as attention mechanisms or transformer-based integrations, to further improve performance and scalability.

International Journal of Basic Science and Technology
December, Volume 10, Number 4, Pages 204 - 212 http://www.ijbst.fuotuoke.edu.ng/ 212
https://doi.org/10.5281/zenodo.17092909
ISSN 2488-86

Conclusion and Recommendation

This study was limited by several factors that could potentially influence the generalizability of the findings. One limitation was the use of a single bilingual English-French dataset, which may not fully represent the diversity of linguistic structures and vocabulary found across other language pairs. Additionally, while the model demonstrated strong performance on the chosen test set, it is unclear how it would perform on datasets involving more complex or domain-specific terminology, such as technical or medical language. The computational resources required for training the hybrid LSTM-GRU model also presented constraints, particularly when dealing with longer sentences and larger datasets, which could affect the scalability of the model in real-world applications.

Despite these limitations, the results indicate that the hybrid Bidirectional LSTM-GRU model offers a promising direction for future research in neural machine translation. To address these limitations, future studies should consider expanding the dataset to include multiple language pairs, especially those with less linguistic overlap, to assess the model's performance across a broader range of language contexts. Moreover, incorporating techniques such as attention mechanisms or transformer-based architectures could potentially enhance the model's ability to handle more intricate linguistic structures and improve overall translation accuracy. Finally, testing the model in real-world, large-scale translation scenarios would help assess its practical applicability and scalability.

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