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Advanced Attention-Enhanced BiLSTM-GRU Model for Real vs. Fake News Detection

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Abstract

INTRODUCTION: Social media has become one of the primary platforms for the rapid dissemination of both real and fake information. In today's digital society, individuals are often easily influenced by misleading content, making fake news a powerful tool for manipulation. A common strategy employed on social media is the intentional spread of false information with the aim of deceiving and misleading the public.

OBJECTIVES: In some cases, this misinformation is so convincing that it significantly influences public opinion and behaviour, with long-term consequences. According to research, only 54% of people are capable of detecting deception without external assistance. To address this growing concern, the proposed model leverages Deep Learning techniques to identify fake news content in both Tamil and English languages.

METHODS: The dataset for this study was sourced from an open-access repository on GitHub. After thorough pre-processing, the dataset was divided into training (80%) and testing (20%) subsets. Additionally, the proposed modified attention-based revamping weighted BiLSTM-GRU model is introduced and evaluated.

RESULTS: The effectiveness of each model is measured using various performance metrics, including accuracy, precision, recall, F1-score, Bilingual Evaluation Understudy, Area under the ROC Curve, and the Receiver Operating Characteristic curve. Comparative analysis shows that the proposed model outperforms the existing methods across all evaluation parameters.

CONCLUSION: A key advantage of the proposed approach is its capability to accurately detect fake text in both Tamil and English. Furthermore, the model demonstrates strong performance when tested on datasets generated using AI tools like ChatGPT, effectively identifying real and fake content with high precision.

Keywords: Fake text, DL (Deep Learning), BiLSTM (Bi-directional Long Short Term Memory), BiLSTM-AM (BiLSTM with Attention Mechanism), GRU (Gated Recurrent Unit), GRU-AM, BiLSTM-GRU

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1. Introduction

Social media has become a widely used platform due to its low cost and easy access. However, consuming news from numerous online articles in different languages presents a double-edged sword. The spread of fake news (1), which is intentionally false information, makes it difficult to discern the truth. Social media fuels this issue by making fake news easy to spread (2), and unfortunately, there's no perfect solution yet. While researchers are developing tools to identify fake news, it remains a complex challenge (3).

Fake news can have serious consequences, affecting public opinion and elections. It gained prominence in

2016 during the US presidential election (4), causing people to question facts and societal norms. While social media companies are taking steps to limit fake news, like removing fake accounts and partnering with fact-checkers (5), there's still no commercially available foolproof detection system.

Studies evaluating various machine learning algorithms, including doc2vec (6), Fake News Tracker (7), Support Vector Machines (SVMs) (8), and decision trees (9), suggest that SVMs and decision trees achieve good accuracy in fake news detection. Research also highlights the negative impact of fake news (10) on public discourse and recommends educating social media users on identifying and avoiding unverified information.

Identifying fake news remains a challenge. Traditional approaches like Naive Bayes and LSTM classifiers (11) (12) are used, and newer language-driven models based on neural networks are being explored to address issues like complex text analysis. These models come with their own limitations, however, such as high computational demands or difficulty handling long-range dependencies in text.

Several methods exist for detecting fake text, but the proposed model offers a unique advantage: it can detect fake news in both Tamil and English languages. The dataset is collected from the public platform GitHub, supplemented with an additional dataset created using AI (ChatGPT). The proposed model compares five different algorithms: BiLSTM (Bi-directional Long Short-Term Memory), BiLSTM-AM (BiLSTM with Attention Mechanism), GRU (Gated Recurrent Unit), GRU-AM, and ANN-FDT (Artificial Neural Network – Fuzzy Decision Tree). The proposed model (modified attention-based, revamped weighted BiLSTM-GRU) achieves superior performance compared to the other models. Notably, the proposed model is also capable of detecting fake text within the AI-generated dataset.

2. Literature Review

In the existing model (13) ,a machine learning ensemble approach has been proposed for automated classification of news articles. Furthermore, usage of textual characteristics that can distinguish between fake and real content has been utilized. Additionally, four real-world datasets has been utilized to propose a better accuracy. Consequently, in the prevailing model (14), an ensemble-based DL (Deep Learning) model for categorizing news as either fake or real, utilizing LIAR dataset has been implemented. Moreover, a Bi-LSTM-GRU-dense DL model has been applied for the textual attribute "statement," and experimental findings have demonstrated that the existing model has achieved an average range of accuracy. Moreover, in the classical model (15), a multimodal approach integrating text and visual analyses of online news stories for automatic fake news detection has been used. Also, experimental outcomes have revealed that a multimodal approach surpasses single-modality methods, facilitating more effective detection of fake news. Likewise, in the existing model (16), a deep CNN (Convolutional Neural Network), a FNDNet tailored for detect the fake news has been introduced, extracting numerous features at each layer, boasting a better accuracy rate. Likewise, in the conventional model (17), a network-oriented pattern-centric approach to fake news detection has been utilized. Furthermore, the experiments have been carried out on two publicly available benchmark datasets, namely PolitiFact and BuzzFeed, achieving an accuracy of approximately 80%. Literally, in the prevailing model (18) the implemented transformer based framework has leveraged information from news articles and social contexts to detect fake news. The experimental outcomes have been attained average performance. Furthermore, to combat the challenge of identifying such misinformation, the existing model (19) has introduced an ensemble classification model designed to detect fake news, has extracted salient features from LIAR dataset exhibiting superior accuracy in comparison to existing methodologies. Consequently, the prevailing model (20) has endeavoured to conduct binary classification on diverse news articles accessible online to predict the fake news in those. Additionally, several publicly available datasets including Buzzfeed News, LIAR and BS Detector have been used. Furthermore, the model has attained an accuracy of 75% using Logistic Regression.

Likewise, in the prevailing model (21), a system involving TF-IDF (Term Frequency-Inverse Document Frequency) of n-grams and bag of words has been modelled as the method of feature extraction, while SVM has served as the classifier. Additionally, a dataset comprising both fake and authentic news has been utilized, exhibiting a better accuracy rate. Likewise, the existing model (22) has presented an automatic approach for detecting fake news within the Chrome environment, focusing on its capability to discern fake news on Facebook. As a result, experimental analysis conducted on real-world data has showcased that the model has surpassed the accuracy of existing state-of-the-art techniques. Subsequently, the prevailing model (23) has used a supervised AI (Artificial Intelligence) algorithm for fake news detection with a dataset containing news has been represented as vectors using Document-Term Matrix and the TF weighting method. The datasets such as ISOT Fake News Dataset, and BuzzFeed Political News Dataset, Random Political News Dataset have been utilized yielding a better performance. Additionally, the prevailing model (24) has utilized a dataset comprising news related to COVID-19, sourced from various social media platforms. Linguistic and sentiment features have been extracted for further processing. However, results have indicated that the RF (Random Forest) classifier performed better than other model with 88.50%. Likewise, in the prevailing model (25), an optimized CNN model, OPCNN-FAKE, has been proposed for detecting fake news. Additionally, four benchmark datasets have been utilized. Furthermore, results demonstrated that OPCNN-FAKE has consistently outperformed other models across each dataset, exhibiting better performance in both cross-validation and testing results. Subsequently, in the prevalent model (26), a hybrid Neural Network architecture combining CNN and LSTM capabilities have been utilized, alongside two distinct dimensionality reduction approaches: Chi-Square and PCA (Principal Component Analysis). Furthermore, dataset acquisition has been extracted from FNC (Fake News Challenges) website. As a result, the existing model has been attained average performance. Likewise, the predominant model (27) has proposed geometric DL for an automatic detection model of fake news. Furthermore, experimentation reveals that social network propagation and structure serve as pivotal features for better accuracy of fake news detection.

Literally, addressing the proliferation and dissemination of fake news, the prevailing model (28) has proposed a hybrid DL model that has integrated CNN and RNN models classify the fake news. Furthermore, the model has utilized two fake news datasets were FA-KES and ISO. In addition, the model has attained approximately 60% accuracy on the FA-KES dataset. Literally, in the existing model (29), a BERT (Bidirectional Encoder Representations from Transformers) based DL approach FakeBERT has been proposed. Additionally, classification outcomes demonstrate that the prevailing model FakeBERT has surpassed existing models, achieving a better accuracy. Furthermore, a multi-level voting ensemble model has been introduced in the prevalent model (30). Consequently, utilizing twelve classifiers the system has been evaluated on three datasets. Moreover, among Logistic Regression, Passive Aggressive and Linear Support Vector Classifiers, the prevailing model outperforms the Passive Aggressive model with a better accuracy. Likewise, in the prevalent model (31), an intelligent detection system called Ensemble Voting Classifier has been introduced. Furthermore, eleven widely recognized machine-learning algorithms, likely Naïve Bayes, K-NN, SVM, Random Forest and others, have been utilized for detection purposes. Correspondingly, experimental results have validated that the proposed framework has achieved an average accuracy. Subsequently, the existing model (32) has explored methods for detecting fake news solely based on text features from real world datasets. Moreover, the observations suggested that through ensemble methods a combination of text-based word vector and stylometric features representations have predicted fake news with an average accuracy. Furthermore, the predominant model (33) has endeavoured to leverage capsule neural networks for the task of fake news detection. The existing model has undergone evaluation on two datasets in the domain: ISOT and LIAR involving a better accuracy rate. Furthermore, the prevalent model (34) has taken into consideration both the content of news articles and the presence of echo chambers in the social network for fake news detection. Consequently, the model has undergone testing on a real-world dataset: BuzzFeed producing an average accuracy rate.

In addition to this, an innovative CNN based semi-supervised framework (35) has been introduced, constructed on the concept of self-ensembling. Furthermore, it has achieved a better accuracy with kaggle dataset. Likewise, the traditional model (36) has introduced a framework for detecting and categorizing fake news messages employing enhanced Recurrent Neural Networks and Deep Structured Semantic Model achieving a better accuracy rate. Correspondingly, in the conventional model (37), deep neural network has been introduced which has been designed to detect fake news early proposing a better performance using real world datasets. Literally, the prevalent model (38) has presented a methodology for analyzing the consistency of information shared on social media during the COVID-19 pandemic situation. Additionally, the model has involved an ensemble of three transformer models XLNET, ALBERT and BERT for detecting fake news achieving an average accuracy. Likewise, the prescriptive model (39) has proposed a CNN model for fake news detection. Moreover, static word embeddings have been compared with non-static embeddings, offering the flexibility of incremental up-training and updating during the training phase. Moreover, the datasets used are ISOT and LIAR. Results from the best architecture has demonstrated encouraging performance, surpassing state-of-the-art methods by 79% on ISOT and 21% on the LIAR dataset's test set. Literally, in the existing model (40), a FDML (Fake News Detection Multi-Task Learning) model has been used. Furthermore, experimental results have indicated that on the real-world fake news datasets FDML model has been attained better accuracy. Initially, news articles have undergone pre-processing and analysis utilizing various training models.

Subsequently, an ensemble learning framework (41) that has integrated four distinct models, aimed at enhancing fake news detection has been introduced. Moreover, to improve detection accuracy, the weights of the ensemble learning model have been optimized using the SAHS (Self-Adaptive Harmony Search) algorithm achieving an average accuracy rate. Likewise, in the existing model, (42) a ML algorithm, SVM for the detection of fake news has been utilized. The recommended research has been used two types of datasets such as CREDBANK and PHEME. In addition, the Buzz Feed's fake news dataset has obtained an average accuracy rate. Correspondingly, in the traditional model (43), three classifiers have been linked after the embedding layer such as CNN, SLP (Single-Layer Perceptron) and MLP (Multi-Layer Perceptron), which have incorporated pre-trained models like GPT2, BERT, Funnel Transformer and RoBERTa. Furthermore, three fake news datasets: COVID-19, ISOT and LIAR datasets have been utilized. As a result, the existing model has achieved an average accuracy rate. The study (44) has developed a two-stage automated pipeline for detecting COVID-19 fake news using advanced machine learning models. The first stage retrieves relevant facts about user claims using a fact-checking algorithm, while the second stage verifies the truth by comparing these claims to a curated COVID-19 dataset. This dataset, containing over 5,000 false claims and verified explanations, was used for training and evaluation. Our results show that a BERT-ALBERT model pipeline yields the best performance in detecting fake news (45).

The study (46, 47) has suggested the Generative Bidirectional Encoder Representations from Transformers (GBERT), which combines GPT and BERT to tackle the fake news classification problem. By integrating BERT's contextual understanding and GPT's generative capabilities, GBERT creates a robust representation of text. Fine-tuned on two real-world datasets, the model achieved 95.30% accuracy, 95.13% precision, 97.35% sensitivity, and 96.23% F1 score. The results highlight the framework's effectiveness, positioning it as a promising approach for addressing the global challenge of fake news (48). Likewise, the prevalent model (44) has used the method of natural language inference (NLI), where several robust NLI models have been individually trained alongside BERT. Furthermore, as a result of the obtained output, the model has achieved a test set accuracy of 88.063%. Likewise, the existing model (49) has aimed to identify fake news within online articles by leveraging semantic features and employing various ML techniques. Furthermore, the model has used a dataset from Kaggle.com and subsequently, RNN has been compared against the Naive Bayes classifier and Random forest classifiers achieving a better accuracy. Consequently, in the prescriptive model (50), a neural network-based model called Multi-View Attention Networks (MVAN) has been implemented. As a result, experimental validation on two real-world datasets have demonstrated that MVAN has surpassed state-of-the-art methods by an average accuracy improvement of 2.5%. Likewise, in the prevailing model (51), an AC-BiLSTM (Attention-based Convolutional Bidirectional Long Short-Term Memory) approach for detecting fake news has been proposed. Evaluated the benchmarked dataset approach has revealed a better accuracy in detection.

The reviewed papers collectively highlight significant advancements in fake news detection using various machine learning and deep learning techniques. Ensemble methods, demonstrate improved accuracy and robustness by combining multiple models. The use of multimodal analysis enriches the detection process by incorporating diverse data types. Additionally, transformer-based approaches and feature extraction techniques, enhance the model's ability to discern subtle semantic cues. Furthermore, the integration of optimized architectures, like CNN-RNN hybrids, showcases the effectiveness of deep learning in tackling the complexities of fake news across different contexts, including social media and urgent topics like COVID-19. Overall, these studies underline the evolving landscape of fake news detection methodologies, emphasizing both innovation and practical applicability. Table.1 shows he Contributions of Existing Researches.

Table.1 Contributions of Existing Researches

Ref.	Technique/Approach Used	Key Contribution / Finding
[40]	Linguistic feature-based learning model	Proposed a model using linguistic features (e.g., syntax, semantics) to improve fake news detection accuracy.
[41]	Decision Tree	Demonstrated the effectiveness of a simple decision tree model in classifying fake news.
[42]	Random Forest & J48 Decision Tree	Compared Random Forest and J48 models; showed good classification performance on fake news datasets.
[43]	Signal Detection Theory (Psychological Perspective)	Provided insight into cognitive mechanisms people use to detect fake news.
[44]	Voting Classifier (Ensemble Learning)	Used ensemble methods (voting) to combine multiple classifiers and improve detection accuracy.
[45]	Naïve Bayes & Effect of Corpus	Explored how different data corpora affect the performance of the Naïve Bayes classifier in fake news detection.
[46]	Support Vector Machine (SVM)	Applied SVM to detect fake news from social media; demonstrated high performance with feature selection.

2.1. Problem Identification

The existing research has been attained the low performance in CNN-LSTM-PCA to analysis the dataset along with the existing research performs poor in larger dataset (26). The limitations of the considered research of CNN-RNN only able to predict the fake news in specific dataset and not good in generalization (28). The limitation of the suggested research was its time complexity during the data process (32) .

3. Proposed Methodology

There are many ML and DL techniques to analyze and predict the fake news or text in online but they have been concentrated only on single language at a time. The dual language ability contains several advancements from the conventional models which focuses on the single language. The proposed model offers dual-language capacity, enabling it to process and analyze text in both Tamil and English, expanding its applicability in diverse linguistic contexts. It incorporates AI-generated datasets, particularly from ChatGPT, to enrich training data and improve accuracy in detecting fake news. By leveraging advanced deep learning techniques and attention mechanisms, the model outperforms existing models, representing a significant advancement in fake news detection. This approach effectively addresses the challenge of multi-language fake news detection while utilizing modern AI techniques to enhance performance. To overcome the challenges such as low performance with the dataset, inability to predict the fake news and limited generalization, the Proposed Classification model (Modified Attention Based Revamping Weighted BiLSTM –GRU analyze the fake text or news in both Tamil and English language. The overall process of the proposed model represented in the figure 1.

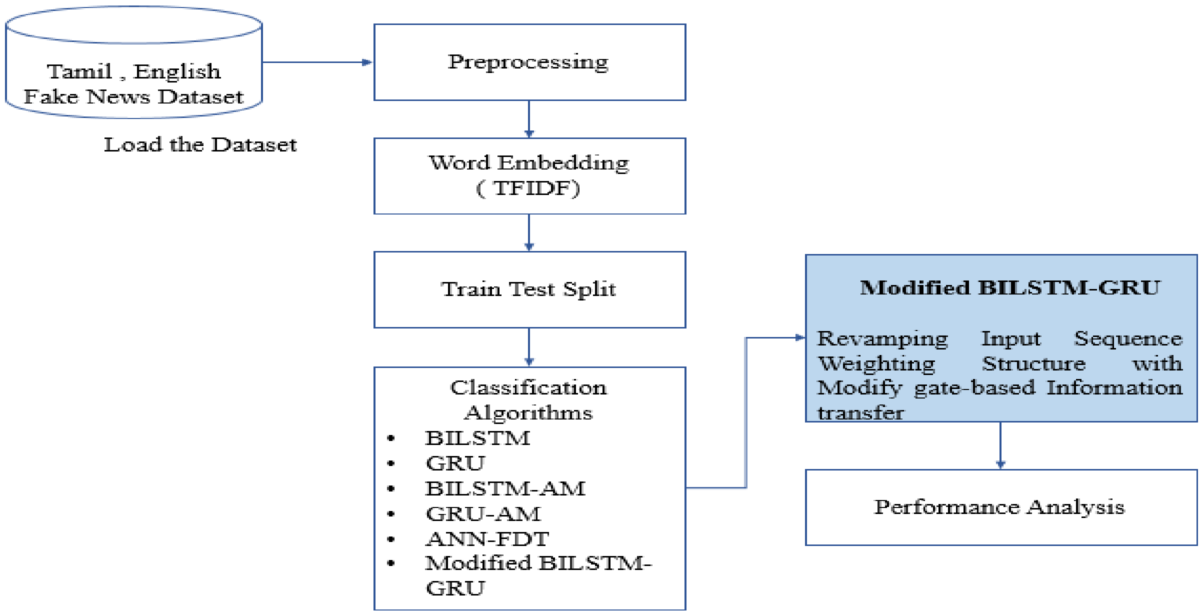


Figure 1. Overall flow of Proposed Model

The figure 1 shows the detail process of the process system. Initially the Tamil and English language dataset are collected from the github. The load and pre-process the dataset to check the missing value and converted into null values. After, pre-processing the processed data splitted into 80:20 ratio for train and split. Secondly, the train dataset fed as an input in classification model. The proposed research compared BiLSTM, GRU, BiLSTM-AM, GRU-AM, ANN-FDT and proposed modified attention based revamping weighted BiLSTM-GRU model in classification process. This algorithm trained the model during the prediction phase the test dataset is include. The efficacy of the model is evaluated by performance metrics overall the proposed modified attention based revamping weighted BiLSTM-GRU model attain high performance.

3.1. Dataset Description

The data is collected from the github website. The link of the dataset is given below for the reference. https://github.com/karthikraja001/Tamil-FakeNews-Prediction. The dataset includes both English and Tamil languages along with fake and real text column and the dataset contains remove punctuation column it includes the set of sentences in both languages. In tokens and filtered tokens, it shows the splitted sentences and in filtered tokens it shows the sentences without stopping words. The rephrased sentence are shown in clean token column and the clean text column shows the corrected sentences. In addition, the dataset also created from chatGPT that includes Tamil and English language and imported into the model. The AI generated dataset is used to analyze the efficient of the proposed model prediction. The size of the dataset depends upon the generated AI text. For instance, the AI generated dataset, Sentence: 34 people have corona in Saidapet Govt Training Center. How is the health of the students? --> Predicted Real or Fake: 0

Sentence: Queen Elizabeth and her husband Prince Philip were found guilty in the disappearance of 10 native children from the Catholic-run Kamloops residential school --> Predicted Real or Fake: 1

3.2. Proposed Classification model (Modified Attention Based Revamping Weighted BiLSTM –GRU)

The proposed research incorporated the BiLSTM with GRU model. The performance of traditional BiLSTM and GRU model attain average performance when compared to the proposed modified attention based revamping weighted BiLSTM – GRU model. The proposed modified attention-based revamping weighted BiLSTM-GRU model introduces an enhancement in the attention mechanism, allowing the model to focus more precisely on the most relevant parts of the input text. By assigning dynamic weights to different segments of the text, the model effectively captures contextually important features while minimizing the impact of irrelevant information. The attention mechanism is designed to adapt to the characteristics of the input, improving accuracy in recognizing patterns in complex sequences. This innovation allows the model to better handle long-range dependencies and intricate textual relationships. Overall, the enhanced attention mechanism significantly improves the performance of the BiLSTM-GRU model for tasks like fake news detection or sentiment analysis.

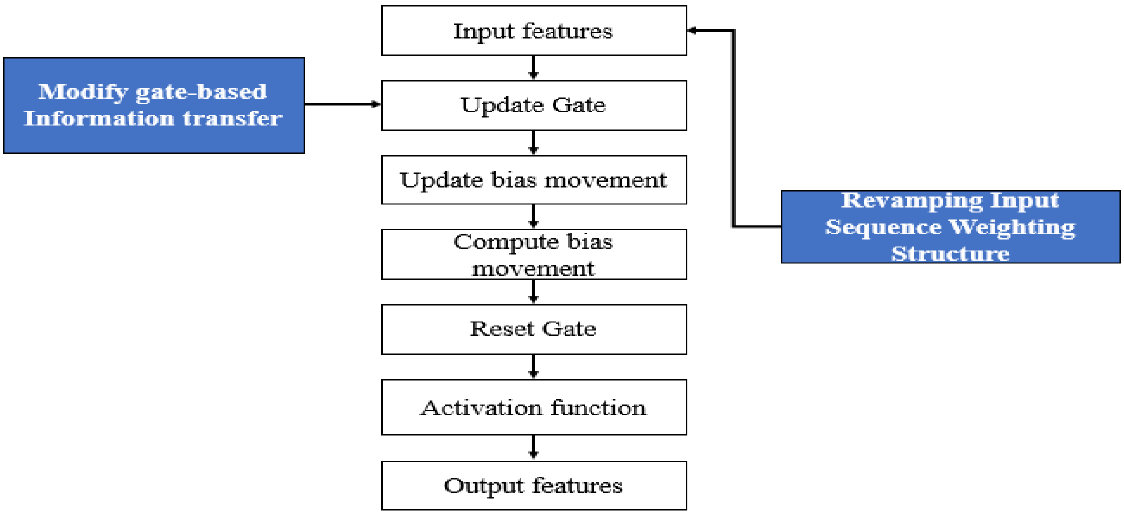


Figure 2. Process flow of Proposed Model

The figure 2 shows the overall process of proposed model. Initially, the revamping input sequence weighting structure method is used in github dataset to change the weighting structure of the dataset for improve the performance of the proposed model by concentrate on only related information. Then, the processed data given as an input feature and fed into the update gate. The modified gate-based information transfer also included in the update gate. During the training phase, to minimize the loss function the bias value adjusted with its weights by update bias movement. It is also known as optimization algorithm. The calculation of the adjusted bias by optimization techniques is attain by the compute bias movement. The processed data entered into the reset gate, while adapting to the current input it allows the GRU to specifically integrate the related information from the previous hidden layer information is reset. In sequential date, this mechanism will efficiently capture the dependences. The activation gate plays a vital role in regulate the information flow through the network to specifically update, retain and forget information along with in sequential data it helps to capture the long-term dependencies. Finally, the processed data reach the output features it includes the information learned from the github dataset ad predict that the given text is real or fake.

At any moment, when calculating the hidden state at initially calculate the candidate state $\tilde{v}_t$. The value of reset gate r_1 is deliberated when calculating the candidate state.

$$r_1 = \sigma(q_r[v_{t-1}, x_t]) \qquad \textbf{(1)}$$

The value of the gate is to limit to [0,1] the sigmoid function is used. The previous hidden state v_{t-1} is avoid by the current candidate value $\acute{v}_t$ if the reset gate is close to 0 then the present input x_t is calculated. In the future, this efficiently permit the hidden state to throw away any unrelated information.

$$\acute{v}_t = tanh(q_h[r_t * v_{t-1}, x_t]) \quad \textbf{(2)}$$

To manage how much information can be transferred from the previous hidden state to the current hidden state by the update gate after calculating the candidate value $\acute{v}_t$. The a_t of update gate is.

$$a_t = \sigma(q_z[v_{t-1}, x_t]) \quad \textbf{(3)}$$

At the current moment the last hidden state v_t can be calculated as.

$$v_t = (1 - a_t) * v_{t-1} + a_t * \acute{v}_t \quad \textbf{(4)}$$

To store and recover information the GRU NN uses the cyclic structure. But the NN cannot deliberate the future moment state it only deliberates past moment information. So the accuracy of prediction not improved. To overcome this problem BiGRU model is used it has future layer which permits to predict the data sequence in the opposite direction. To extract information from the past and future the network uses two hidden layers both are connected in the same output layer.

$$\vec{v}_t = GRU(x_t, \vec{v}_{t-1}) \quad \textbf{(5)}$$

$$\acute{v}_t = GRU(x_t, \acute{v}_{t-1}) \quad \textbf{(6)}$$

$$v_t = u_t\vec{v}_t + v_t\acute{v}_t + b_t \quad \textbf{(7)}$$

The function signifies the non-linear transformation of the input data among the hidden layers. The weights respective to the forward hidden layer are denoted by u_t and v_t. The reverse hidden layer is denoted by $\vec{v}_t$, the hidden layer state is denoted by b_t and the time denoted by t. At the current time to evaluate the attention weight corresponding to each h, into the attention mechanism fed hidden state V and encompass the output y'_{i-1} of BiGRU at time i. In the encoder, y'_0 is attained from the last hidden state v_m. The weight calculation derived below.

$$e_{ij} = V^T tanh\left(qh_j + Uy'_{i-1} + bias\right), i \in N, 1 \le i \le n, j \in N, 1 \le j \le m \quad \textbf{(8)}$$

Here, the learnable weight matrices are $V \in R^T, q \in R^{T\times k}$ and $U \in R^{T\times k}$.

According to equation (8), to normalize e_{ij} Soft max function is used.

$$a_{ij} = \frac{exp\,(e_{ij})}{\sum_{j=1}^{m} exp\,(e_{ij})} \quad \textbf{(9)}$$

The attention mechanism pseudo code is shown in algorithm 1.

Algorithm 1. Pseudo Code for Proposed Attention Mechanism

```
Hidden = encoder.bigru.output
y'_0 = h_1
for i = 1 to TargetLength do
    for j = 1 to InputLength do
        e_ij = MLP(y'_{i-1}, h)
    endfor
    A_i = exp(e_ij) / Σ_{j=1}^{TargetLength} exp(e_ij)
    c_i = A_i Hidden
    y'_i = f_2(c_i, y'_{i-1})
endfor
return Y'
```

The algorithm 1 shows the pseudo code for attention mechanism. The f_2 is denoted BiGRU unit in the decoder. The weighted data deliberating the influence original cell state size but the input is no longer. To enhance the prediction accuracy through attention mechanism by excerpts the contribution rate of each input data. The advantages of the proposed Modified Attention Based Revamping Weighted BiLSTM –GRU is detecting fake text in both Tamil and English, which is main for multilingual applications. The modified attention-based approach enhances the model's ability to focus on relevant parts of the text, potentially improving detection accuracy. Utilizes a dataset created by AI (like ChatGPT), which will provide diverse and used for training. In contrast to other baseline models, the proposed Modified Attention Based Revamping Weighted BiLSTM –GRU has given better performance.

4. Result and Discussion

This section includes the experimental results of proposed modified attention based revamping weighted BiLSTM- GRU model with performance metrics, EDA (Exploratory Data Analysis), performance analysis and comparative analysis.

4.1. Performance Metrics

This section includes the experimental results of proposed model. The efficiency of proposed model is evaluated by the performance metrics such as accuracy, precision, recall, F1 – score and ROC – curve.

4.1.1. Accuracy

Across all the classes, accuracy metric is used to provide the model measure. The

- True Negative rate represented by the Tr_N
- True Positive rate represented by the Tr_P
- False Negative rates represented by Fl_N
- False Positive rates represented by Fl_P

The overall accuracy assessed using,

$$Accuracy = (Tr_P + Tr_N)/(Tr_P + Tr_N + Fl_P + Fl_N) \quad (10)$$

4.1.2. Precision

The important metrics for model performance are instances and the precision is used for saving the information and given using,

$$Precision = Tr_P/(Tr_P + Fl_P) \quad (11)$$

4.1.3. Recall

In the proposed model, to define the model detecting the total number of false and true incidents of the positive instances the metric is used.

$$Recall = Tr_P/(Tr_P + Fl_N) \quad (12)$$

4.1.4. F1-Score Recall

The weighted harmonic mean value of recall and precision is signifies by F1 score. It is valued with the following equation.

$$F1 - score = 2 \times (RC \times Pc)/(Rc + Pc) \quad (13)$$

Here, R is denoted as recall and P is denoted as precision.

4.2. EDA (Exploratory Data Analysis)

The corresponding section includes the graphical representation of the proposed model.

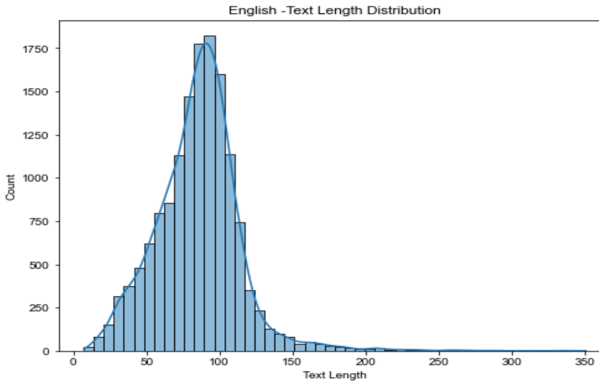


Figure 3. English text Length Distribution

The figure 3 shows the English text length distribution of the text length of 95 has the highest count of 1800. From 0 to 95 the count gradually increased and from 95 to 200 the count is gradually decreased.

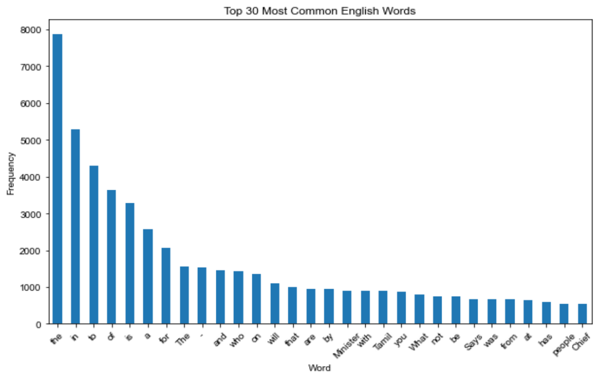


Figure 4. Top 30 English Words

The figure 4 shows frequently used top 30 words, it shows “the” word used often with the frequency of 7900. The “in” word is second frequently used word with the frequency of 5300. Finally, the last word in top 30 words is “Chief” with the frequency of 500. The figure 5 shows the frequently used word in English language in both fake and real texts.

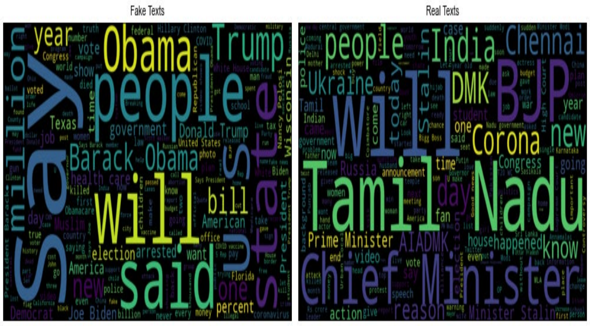


Figure 5. English Word Cloud

Table. 2 Contributions of BiLSTM, GRU, and attention mechanisms

Model Configuration	Accuracy	Precision	Recall	F1-Score	Key Components
Modified Attention-based BiLSTM-GRU (Proposed)	**0.96**	**0.94**	**0.95**	**0.94**	**- Complete hybrid architecture Modified attention mechanism Revamping weights**
BiLSTM-AM	0.94	0.88	0.81	0.84	- BiLSTM base Attention mechanism
BiLSTM	0.93	0.83	0.84	0.84	- Basic BiLSTM architecture
ANN-FDT	0.93	0.82	0.83	0.86	- Neural network Fuzzy decision tree
GRU	0.92	0.81	0.77	0.79	- Basic GRU architecture
GRU-AM	0.92	0.83	0.76	0.79	- GRU base Attention mechanism

Table.2 depicts the performance metrics of the other model's with the proposed model and demonstrating the key components where the proposed modified attention based BiLSTM-GRU has obtained 0.96 of accuracy, 0.94 of precision, 0.95 of recall and 0.94 of F1 score with the complete architecture and modified attention mechanism along with the revamping weights**.**

Table. 3 Computational Complexity

Models	Computational Complexity
BiLSTM (Bi-directional Long Short Term Memory)	O(T·(n2+m))*O*(*T*·(*n*2+*m*))
BiLSTM-AM (BiLSTM with Attention Mechanism)	O(T·(n2+m+k))O(T·(n2+m+k))
GRU (Gated Recurrent Unit)	O(T·(n+m))O(T·(n+m))
ANN-FDT (Artificial Neural Network – Fuzzy Decision Tree)	O(n·m2)*O*(*n*·*m*2)
GRU-AM (GRU with Attention Mechanism)	O(T·(n+m+k))*O*(*T*·(*n*+*m*+*k*))
Modified Attention Based Revamping Weighted BiLSTM-GRU Model	**O(T·(n2+m+k+p))*O*(*T*·(*n*2+*m*+*k*+*p*))**

Table.3 depicts the computational complexity of the proposed model with the existing models where T*T* denotes Number of time steps, n*n* denotes the Number of input features, m*m* denotes Number of hidden units, k*k* denotes the Number of attention weights (usually proportional to the sequence length), m*m* denotes the Number of hidden units and p*p* denotes the Additional complexity introduced by modifications and weight adjustments.

- The scalability in ML models involves addressing several key factors to ensure performance remains optimal as datasets grow.
- Computational efficiency is crucial, as increasing data sizes often lead to longer training times. Using advanced techniques like mini-batch training or leveraging GPUs can significantly reduce these times.
- Memory management becomes another challenge, as large datasets demand substantial memory resources. To handle this, efficient data structures, such as sparse matrices or compressed formats, can optimize memory usage.

Additionally, the algorithm complexity of certain models can hinder scalability, especially if they have high computational demands. To improve scalability, it is important to choose or develop models with lower computational complexity and optimize them for larger datasets.

4.3. Performance Analysis

This section analyzes the performance of the proposed model (Modified Attention Based Revamping Weighted BiLSTM- GRU). The analysis is presented visually using confusion matrices, model plots, and ROC curves.

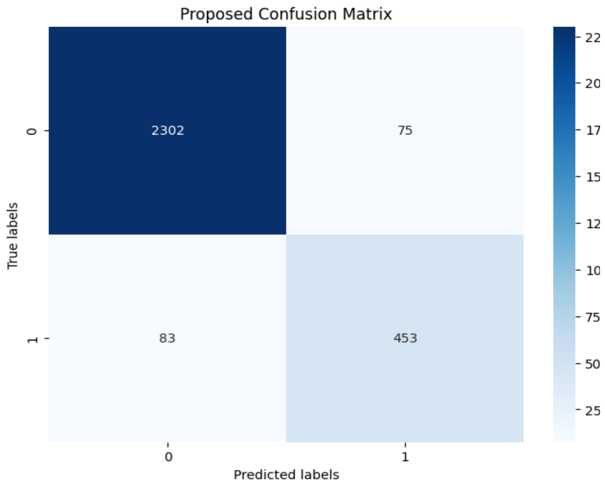


Figure 6. Confusion Matrix for Proposed Model – Tamil

The figure 6 shows the confusion matrix of proposed modified attention based revamping weighted BiLSTM-GRU model for Tamil language between predicted labels and true labels. The TP value is 2302, FP value is 75, FN value is 83, and TN value is 453.

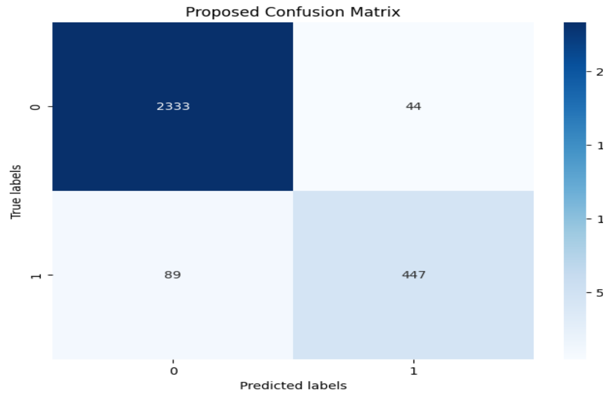
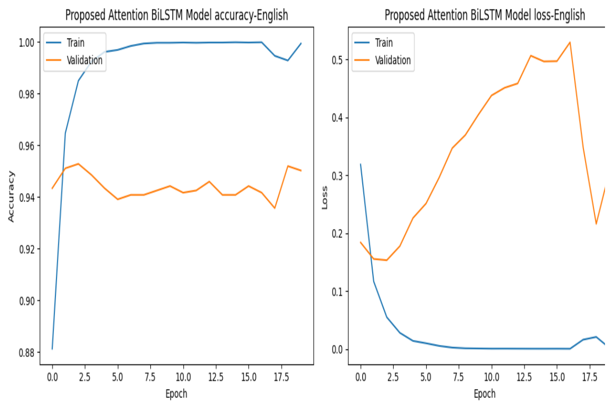


Figure 7. Confusion Matrix for Proposed Model – English

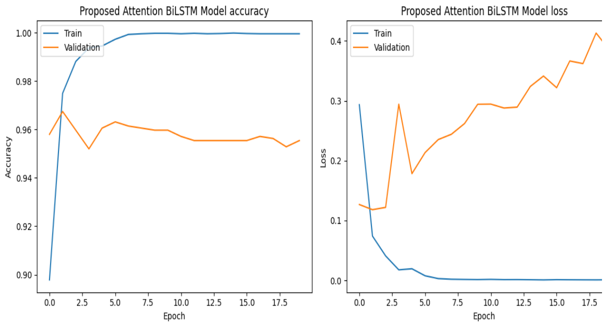
The figure 7 shows the confusion matrix of proposed modified attention based revamping weighted BiLSTM-GRU model for English language between predicted labels and true labels. The TP value is 2333, FP value is 44, FN value is 89, and TN value is 447.



(a) (b)

Figure 8. Model Plot for Proposed Model – English

The figure 8 (a) shows the model accuracy of proposed modified attention based revamping weighted BiLSTM-GRU model in English language during train and validation loss. The proposed model attain best performance. The figure 8 (b) shows the model loss of proposed modified attention based revamping weighted BiLSTM- GRU model during train and validation accuracy. The proposed model attain best performance in model loss.



(a) (b)

Figure 9. Model Plot for Proposed Model – Tamil

The figure 9 (a) shows the model accuracy of proposed modified attention based revamping weighted BiLSTM-GRU model in Tamil language during train and validation loss. The proposed model attain best performance. The figure 9 (b) shows the model loss of proposed modified attention based revamping weighted BiLSTM- GRU model during train and validation accuracy. The proposed model attain best performance in model loss.

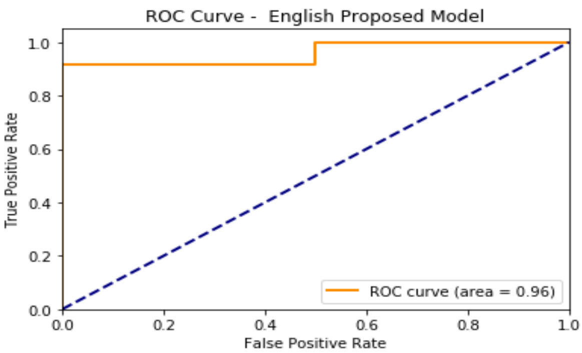


Figure 10. ROC Curve for Proposed Model – English

The figure 10 shows the respective ROC curve that deliberate the values of confusion matrix of proposed modified attention based revamping weighted BiLSTM-GRU model for English Language. It shows the ROC curve and random guess of proposed model confusion matrix. The performance of proposed modified attention based revamping weighted BiLSTM- GRU model attain best performance. The ROC curve area of proposed model is 0.96.

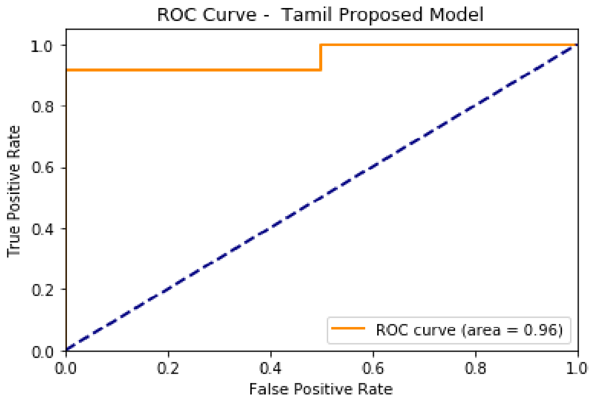


Figure 11. ROC Curve for Proposed Model – Tamil

The figure 11 shows the respective ROC curve that deliberate the values of confusion matrix of proposed modified attention based revamping weighted BiLSTM- GRU model for Tamil Language. It shows the ROC curve and random guess of proposed model confusion matrix. The performance of proposed modified attention based revamping weighted BiLSTM- GRU model attain best performance. The ROC curve area of proposed model is 0.96.

Model	Accuracy	Precision	Recall	F1-Score	BLEU		AUC	
					Tamil	English	Tamil	English
Proposed	0.96	0.94	0.95	0.94	0.75	1.0	0.89	0.88

Table 4. Performance Analysis of Proposed Model

The table 4 shows the performance of proposed model in accuracy, precision, recall, F1-Score, BLEU (Tamil, English) and AUC (Tamil, English) are 0.96, 0.94, 0.95, 0.94, (0.75, 1.0) and (0.89, 0.88).

Table 5. Comparison of Proposed Model in Tamil Language

Model	Accuracy	Precision	Recall	F1-Score
BILSTM	0.93	0.83	0.84	0.84
GRU	0.92	0.81	0.77	0.79
BILSTM-AM	0.94	0.88	0.81	0.84
ANN-FDT	0.93	0.82	0.83	0.86
GRU-AM	0.92	0.83	0.76	0.79
Proposed	0.96	0.94	0.95	0.94

Table.5 presents the performance metrics of various models used for classification, showcasing their Accuracy, Precision, Recall, and F1-Score. The Proposed model achieves the highest accuracy at 0.96, indicating that it correctly predicts 96% of the instances. It also excels in Precision and Recall, with values of 0.94 and 0.95, respectively, suggesting a strong ability to identify true positives while minimizing false positives. BILSTM-AM follows closely with an accuracy of 0.94, a Precision of 0.88, and a Recall of 0.81, demonstrating solid performance. In contrast, the GRU model shows lower performance across all metrics, with an accuracy of 0.92, Precision of 0.81, and Recall of 0.77. Overall, the proposed model stands out as the most effective, significantly outperforming the other models in key evaluation criteria.

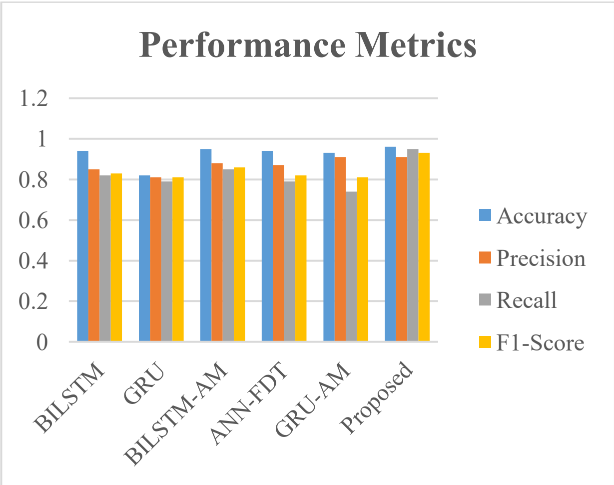


Figure 12. Comparison between Proposed and other Models – Tamil

Table 6. Comparison of Proposed Model in English Language

Model	Accuracy	Precision	Recall	F1-Score
BILSTM	0.94	0.85	0.82	0.83
GRU	0.82	0.81	0.79	0.81
BILSTM-AM	0.95	0.88	0.85	0.86
ANN-FDT	0.94	0.87	0.79	0.82
GRU-AM	0.93	0.91	0.74	0.81
Proposed	0.96	0.91	0.95	0.93

Table.6 summarizes the performance metrics of various classification models, highlighting their Accuracy, Precision, Recall, and F1-Score. The Proposed model leads with an impressive accuracy of 0.96, reflecting its ability to correctly classify 96% of instances. It also demonstrates high Precision at 0.91 and Recall at 0.95, indicating a strong capacity to identify relevant instances while maintaining low false positives. Following closely is the BILSTM-AM model, which achieves an accuracy of 0.95, with Precision at 0.88 and Recall at 0.85, showing robust performance. The BILSTM model has an accuracy of 0.94, with Precision at 0.85 and Recall at 0.82, while the ANN-FDT model matches this accuracy but has slightly lower Precision and Recall values. The GRU model shows the lowest accuracy at 0.82, along with a Precision of 0.81 and Recall of 0.79, indicating less effectiveness compared to the other models. Overall, the Proposed model outperforms the rest across all key metrics, suggesting it is the most effective choice for the given classification task.

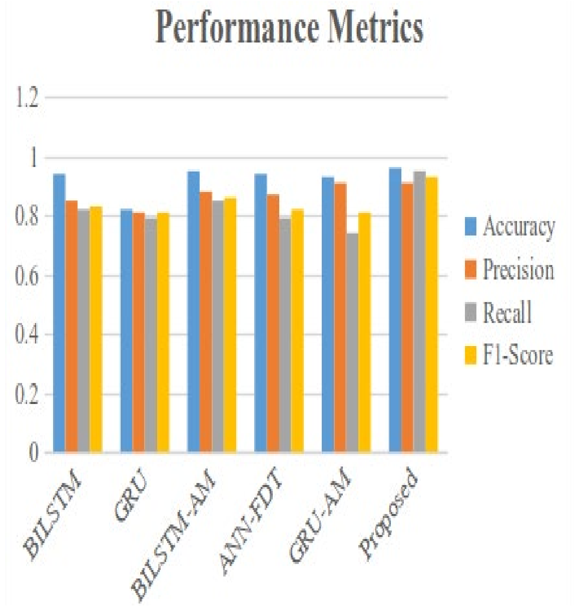


Figure 13. Comparison between Proposed and other Models – English

Discussion and Practical Implications

The Modified Attention-Based Revamping Weighted BiLSTM-GRU Model introduces key innovations for fake news detection. It features an Enhanced Attention Mechanism that dynamically assigns context-aware weights to bilingual (Tamil and English) input tokens, improving contextual relevance and reducing noise. The model also employs a Revamping Input Sequence Weighting Structure, where pre-processing amplifies relevant features before attention, ensuring prioritized inputs. Additionally, Modified GRU Gating with Optimized Bias Movement enhances convergence by dynamically adjusting gate behaviours, addressing vanishing gradient issues. The model's Multilingual Capability makes it one of the few tailored for low-resource languages, like Tamil, improving generalization. Finally, it is evaluated using Advanced Metrics (e.g., BLEU, AUC, and ROC), offering a more comprehensive performance analysis beyond traditional accuracy and F1-score. The Modified Attention Based Revamping Weighted BiLSTM –GRU model shows high accuracy in detecting fake news in Tamil and English, deploying it in real-time systems presents several practical considerations. Real-world applications require low-latency inference, which may be constrained by the model’s complexity and memory usage, specifically on edge devices or low-resource environments. Additionally, adapting the model to new languages involves retraining or fine-tuning with language-specific embeddings and datasets, which may not always be readily available for low-resource languages. Despite these challenges, the model's modular design allows it to be fine-tuned and scaled with appropriate engineering for multilingual, cross-platform fake news detection.

5. Conclusion and Future recommendation

In our day-to-day updates, both real and fake news are combined, but most of the time we are not aware of that information. There are some traditional techniques to analyze the text, but it has been a time-consuming process. To overcome this issue, the proposed model used DL techniques to analyze the real and fake text in both English and Tamil. The dataset was collected from GitHub along with another set of datasets created by using ChatGPT. The proposed model has used the modified attention-based revamping weighted BiLSTM-GRU model, in which a modified attention mechanism has been used to distribute the processed data to the layers depending upon its weight to detect the real and fake text in both Tamil and English. The proposed model has been compared to four DL models with the proposed model, namely BiLSTM, BiLSTM with AM, GRU, GRU with AM, and the proposed modified attention-based revamping weighted BiLSTM-GRU model. The overall performance of the proposed modified attention-based revamping weighted BiLSTM-GRU model attains the best performance in accuracy, precision, recall, BLEU, AOC, and F1-score in both Tamil (0.96, 0.94, 0.95, 0.75, 0.90, 0.94) and English (0.96, 0.91, 0.95, 1.0, 0.91, 0.93). Additionally, the proposed model has been able to predict the real and fake text in the AI-generated dataset with high accuracy in both Tamil and English. The collected data has been processed with the phase 1 algorithm of ANN-FDT (ANN-Fuzzy Decision Tree). The algorithm has attained accuracy in Tamil (93%) and in English (94%). The future work of the proposed research will aim to attain better classification in text by advanced ML and NLP methods. In addition, the proposed research focuses on detecting refined fake text, such as manipulated media and deep fakes.

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Data Availability Statement – Not Applicable
Research Involving Human and /or Animals – Not Applicable
Informed Consent- – Not Applicable

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