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Research Article

Design an Optimized Deep Learning Architecture to Identify Clinical Implications of Adverse Drug Reaction

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ABSTRACT

Adverse drug reactions (ADRs) represent considerable public health risks, demanding appropriate monitoring and detection systems. The abundance of user-generated comments on social media platforms provides a viable route for early identification and monitoring of ADRs. This study suggests a hybrid classifier that uses machine learning (ML) and deep learning (DL) approaches combined with social media data to improve ADR detection accuracy. The hybrid classifier model consists of a Recurrent Neural Network (RNN) and a Bi-directional Long-Short Term Method (Bi- LSTM). Social media platforms are a new kind of information source that gives people access to up-to-the-minute data, but they also bring new problems, such as noise and unstructured data. There is a lack of all-inclusive algorithms that can analyze structured and unstructured data to identify ADRs. There is a big obstacle here. Data from several internet message boards is gathered, organized and unstructured data is processed, and keywords are extracted to guarantee correct classification as part of the investigation's multi-pronged strategy. Some feature extraction methodologies include WordNet, TF-IDF, Semantic Similarity, Higher-Order Statistical Features, and Sentiment Analysis. The results validate the usage of the hybrid classifier and show that it is more effective than conventional approaches in ADR recognition, with an accuracy level of 95.6%. A portion of the system enhanced overall performance could be attributed to the Improved Rider Optimization algorithm.

Keywords: Improved Rider Optimization, RNN, Adverse drug reaction, Bi-LSTM, Social media.

INTRODUCTION

Adverse drug responses (ADRs) are unplanned unpleasant effects of a medicine or other intervention, such as surgery. An estimated 2 million significant ADRs among hospitalized patients occur annually in the United States, leading to over 100,000 fatalities[1]. In the United States and other industrialized nations, ADRs are quickly rising to the top of the list of causes of death[2]. According to current data, ADRs harm the public's access thealthcar irreversibly. Every year, ADRs are responsible for up significant amount of money as a consequence of ADR-caused medication recalls; these losses total around $7.5 billion yearly. Fortunately, a meta-analysis indicates that robust monitoring could prevent around half of all ADRs [6]. Therefore, it is crucial to promptly and accurately oversee medication safety after it has been commercialized. In this case, social media provide a significant quantity of data for ADR detection via the use of NLP. Among these social media is Twitter, which is a useful data source for a variety of topics, including tweets and debates about ADR. As of right now, 342,000,000 active users and 135,000 registered users use Twitter every day. It has been shown that most patients voluntarily contributed information about their health status on various medical websites that are accessible to the public, or open forums like Twitter, the "Ask a Patient" website, etc., which offered a useful tool for tracking ADRs. However, the language and writing style employed to convey this kind of information make it challenging to extract valuable information from social media. They greatly enhance ADR detection via social media, which reduces the need for human data labeling, even if the development of an appropriate model as a monitoring tool usually involves vast amounts of data and medical specialists. In this study, they gathered a wide range of comments and used a hybrid classifier to automatically analyze them. The emergence of social media platforms, such as Twitter, during the last ten years, has transformed online communication and networking. These platforms are being utilized for digital disease monitoring real-time trend tracking and information retrieval. One of the most widely used social media platforms is Twitter, which can be used as a real-time resource for ADR detection. Nevertheless, there are several difficulties in finding ADRs in tweets. Examples include the following: (1) the sparsity of ADR tweets in real-world Twitter streams; (2) the informal description of health problems; and (3) the inclusion of ailments and medications in the same tweet, without necessarily indicating an ADR. This work performs highly accurate ADR detection using an LSTM and RNN classifier with multiple extracted features. To improve the quality of the training process, the texts from the dataset are first preprocessed. In the preprocessing stage, unwanted text characters and keywords are removed. Various features, including semantics, and text statics. Social media comments are extracted from various networks to study the performance of the proposed ADR implementation process. The sensitivity evaluation technique is applied to the classified labels to evaluate the performance of the proposed techniques. They suggested a hybrid classifier (RNN and Bi-LSTM) for the detection of ADRs in this research. Along with the collecting of data from many sources, such as the records kept by the Clinical Pharmacy Department, PubMed, and social media forums, one of the goals here is to develop an advanced hybrid classifier that is capable of accurate ADR detection. Ultimately, the outcome is determined by several parameters such as recall, accuracy, precision, and f1-score. The study follows the following structure: In Section 2, the authors provide a literature assessment of current methods that use several techniques for ADR detection. The study methodology and methods are offered in Section 3, and the latter for the anticipated findings with comparison analysis. Finally, the paper gives a conclusion and suggests areas for further research.

ADR Classification

The rise in healthcare expenses, morbidity, and death caused by ADRs is a major cause for concern. Better understanding, prediction, and prevention of these catastrophes have led to the development of numerous categorization systems throughout the years. Two systems that are often cited are the Rawlins and Thompson schemes. In 1977, Rawlins and Thompson established a system to classify ADRs into two groups: Type A and Type B[7]. The majority of ADRs are type A, which are dose-dependent and predicted according to a medicine's known pharmacological activities. Type B responses, on the other hand, are less prevalent, unexpected, and dose-independent; when they occur, they are often severe enough to necessitate stopping the medicine[8,9]. This kind of ADR would be challenging to categorize using the Rawlins and Thompson categorization because it relies on individual genetic susceptibility rather than being strictly dose-dependent or predicted based on the drug's known pharmacology. Figure 1 shows the majority of ADRs that occur as well as drug-induced toxicities.

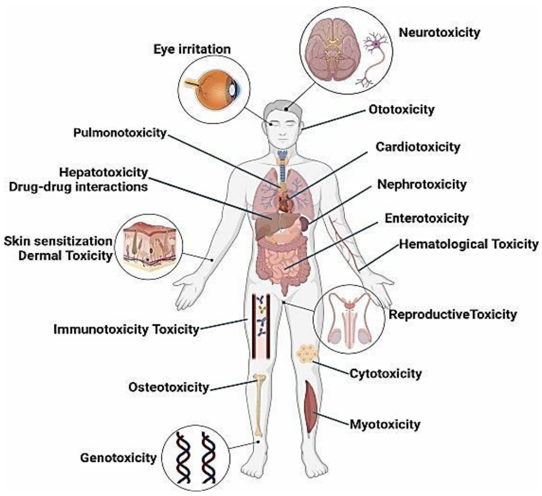

Figure 1: Human systemic ADRs and drug-induced toxicities [10].

LITERATURE REVIEW

Previously, several techniques were proposed to perform highly accurate ADR implementation. Various techniques used different pre-processing and feature extraction algorithms to achieve high accuracy. The major challenges in

ADR classification are computational time and accuracy. Some techniques achieved acceptable accuracy with high computational complexity. Other techniques achieved moderate accuracy with less computation time. The computational time and accuracy should be balanced to obtain high performance of the ADR classification. The following session describes detailed information about the previous works performed.

McMaster et al., (2023)[11] created a system for ADR detection in academic hospital discharge summaries using DL and natural language processing. An earlier published RoBERTa model pre-trained on MIMIC III, which has shown good performance on other pharmacovigilance tasks, and a version of the model that did not include the pre-training phase was compared to this version. Outperforming the two comparison models by a wide margin, the final model showed high performance with an ROC-AUC of 0.955 (95% CI 0.933 - 0.978) for the task of recognizing discharge summaries including ADR mentions.

Liu et al., (2022)[12] presented a Deep Attention Neural Network based Drug-Drug Interaction (DANN-DDI) prediction framework to predict unobserved DDI. When compared to state-of-the-art techniques, the investigational findings show that the model, DANN-DDI, has enhanced prediction performance. Furthermore, new drug-drug interactions as well as events linked to drug-drug interactions could be predicted by the suggested model.

Lin et al., (2022)[13] provided an innovative approach, MDF-SA-DDI, that uses a transformer self-attention mechanism, multi-source feature fusion, and multi-source drug fusion to forecast DDI occurrences. They used two datasets to test three distinct tasks. With an area under the precision-recall-curve (AUPR) of 0.9737 and an F1 score of 0.8878 on task 1, the technique outperformed the other method on the tiny dataset. On the first task, the technique achieved an AUPR of 0.9773 and an F1 score of 0.9117 on the huge dataset. They also found that the technique outperformed the other methods in tasks 2 and 3 of the two datasets.

De et al., (2021)[14] suggested technique sources out to establish correlations between disparate data sets that have varying degrees of trustworthiness. The approach uses Fuzzy Formal Concept Analysis (Fuzzy FCA) to assess the credibility of adverse medication occurrences retrieved from Twitter and PubMed. According to the official site, the key finding is that 91% of the medication and side effect correlations retrieved from tweets can be regarded credible when τ is in the range $[-4, +4]$.

Wei et al., (2020)[15] described the methods for extracting drugs and their related ADEs from records related to patient care. They experimented with DL-based methods (e.g., BI-LSTM-CRF) and compared them to more conventional ML methods, such as support vector machines (SVM) for RC and conditional random fields for NER. Achieving F1 scores of 96.30% for RC, 89.05% for end-to-end assessment, and 93.45% for NER were the top-performing systems.

Zhang et al., (2021)[16] provided a framework for adversarial transfer that moves auxiliary characteristics from PubMed to social media datasets to improve the model's generalizability and reduce noise from informal speech on social media. This framework would be useful for ADR identification. Two datasets from social media and two datasets from PubMed are used for the experimental evaluation of the strategy that they presented. The results demonstrate that the suggested approach could improve the efficiency of ADR detection using social media.

Li et al., (2020)[17] developed a successful strategy for identifying ADRs in medical tweets by combining adequate emotional expression with medical expertise. Lastly, the classification job was carried out using a CNN model that was built on Bidirectional Encoder Representations from Transformers (BERT). Using two Twitter datasets, the suggested model performs better than the other approaches with F1 scores of 72.64% on PSB2016 and 64.98% on SMM4H.

The primary objectives of this research are

- To compile ADR information from several sources, such as the Clinical Pharmacy Department. Social Media or PubMed
- Preprocess the information so that unstructured and structured data can be analyzed.
- To identify the relevant keywords from the raw data to effectively categorize the ADRs.
- To examine feature extraction for greater accuracy utilizing Sentiment Analysis, Word Net, Higher Order Statistical Features, Semantic Similarity, and Term Frequency–Inverse Document Frequency (TF-IDF).

- To increase the accuracy of ADR detection by creating a hybrid classifier based on the Deep RNN –Bi-LSTM deep learning approach.
- To find a better rider optimization technique to improve the classifier's performance.

MATERIAL AND METHODS

This section defines the proposed methodology based on ADR detection. Figure 2 shows the flow chart of the proposed work.

Dataset

Event Corpus (CADEC) is a brand-new, all-encompassing corpus of the comments that have been made on medical forums on adverse drug events that have been reported by patients (ADEs). The content that is included in the corpus is mostly composed of postings on social media platforms, and it often deviates from the rules of normal English syntax and punctuation. Additionally, the majority of the material is written in simple language [18]. Annotations and linked ideas from limited vocabularies refer**.** To a variety of topics, including medications, adverse effects, symptoms, and diseases [19,20]. It is possible to expedite the processes of training by using clusters of high-performance computers to carry out the simulations, as shown in Table 1.

Table 1: Experimental Setup

Parameter	Value
Training Epochs	100
Batch size	128
Learning Rate	0.001
Optimizer	Adam

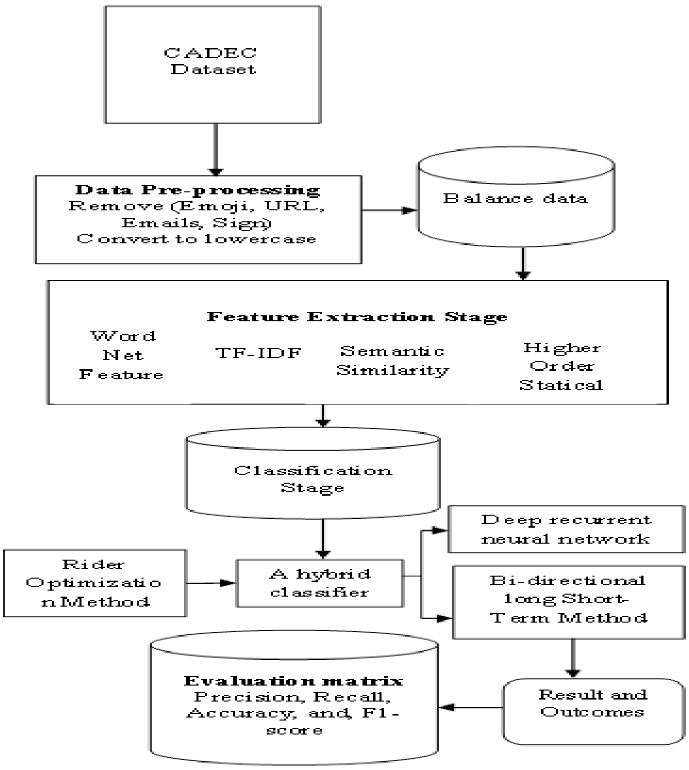

Figure 2: Proposed Work

Data Pre-processing

The following procedure was used to pre-process the comments in three datasets:

Data shuffles

All capital words are converted to lowercase, and special characters like @, /, *, $, etc. are removed.

The stop words at, of, the, and Fixing words that include repeated characters, such as "yes" or "please."

Convert acronyms and abbreviations to their full form, as in "I'm →."I am.

Lemmatization: "I started taking almost two months ago," for example, translates to "I started to take almost two months ago."

Feature Extraction

An essential part of analysing and interpreting text is the process of extracting characteristics. To improve classification accuracy during ADR detection, it is crucial to extract important characteristics from the raw text.

Word Net: Word Net is a lexical database that records words that are related in the English language. All of these terms are stored in Word Net. These terms are connected and include synonyms, hypernyms, hyponyms, and other similar words. The method of feature extraction could be applied to uncover relationships between words, and Word Net can be utilized to do this. Semantic capture benefits from the system's enhanced understanding of phrase context and word relationships about hazardous pharmaceutical effects.

Term Frequency-Inverse Document Frequency (TF-IDF): TF-IDF is a statistic that compares the frequency with which a phrase occurs in one document to the frequency with which it is found in a different document. This comparison is made using the term frequency. It is possible to use the TF-IDF to determine the significance of certain phrases when it comes to the detection of ADR. When categorization is being done, words that occur often in a specific document but less frequently in the collection are given a larger amount of weight than terms that appear regularly in the collection.

Semantic Similarity: The semantic similarity of two texts is measured using this metric, which indicates the extent to which the implications of the texts are comparable to one another. Using this approach of feature extraction could prove beneficial when it comes to deciphering the meaning of phrases that are used to describe the unwanted side effects of medicine. Therefore, by taking into account the context of the dataset as well as the similarity of terms, it is possible to construct a more advanced analysis.

Higher-Order Statistical Features: The extraction of statistical characteristics that go below the measurement of basic frequency yields higher-order statistical features. These features are formed by the extraction of empirical attributes. To do this, it could be necessary to investigate more complex word patterns, distributions, and connections. The method of feature extraction can recognize and extract more complex data patterns and structures than it was previously capable of doing when higher-order statistics are considered.

Hybrid Classifier Development

It is necessary to design a model for classification to create a hybrid classifier. This model must integrate the most favorable parts of several distinct techniques or algorithms. To accomplish the aim of making use of both tried and tested approaches as well as the most cutting-edge ML algorithms, the objective of building a hybrid classifier for ADR detection is to achieve the goal. It is a recurrent neural network (RNN) with a bidirectional long short-term memory (Bi-LSTM) architecture that serves as the foundation of the hybrid classifier that is advocated and provided in this research[21]. In the field of natural language processing, RNNs are best suited for employment because of their capacity to perform well with sequential input. RNNs can capture the sequential component of textual input, which is an essential component for the detection of ADR. The arrangement of words inside words or documents, in addition to the context in which they are embedded, is considered to achieve this goal[22].RNN-LSTM provides a solution to the problem of vanishing gradients, which allows them to successfully capture long-term relationships in sequential data. The phrase "bidirectional" refers to the fact that the network is capable of processing data arriving from both directions, which is the origin of the label. Since it can better comprehend the context and the connections included within the text, the model benefits from this two-way processing.The hybrid classifier allows for the best features of both classical approaches and DL to be combined into a single methodology. Statistical models, rule-based systems, and feature extraction approaches are only a few examples of the conventional methods that fall under this category of methodology. DL can recognize complicated patterns in data, which is the goal of the hybrid classifier.

The hybrid classifier's goal is to capitalize on the advantages that are supplied by both classical approaches (such as their discernibility and accuracy) and DL. The computation for the gates is[23]:

$$G_i^t = \sigma(w_i x^t + U_i h^{t-1} + b_i) \tag{1}$$

$$G_f^t = \sigma\left(w_f x^t + U_f h^{t-1} + b_f\right) \tag{2}$$

$$G_o^t = \sigma(w_o x^t + U_o h^{t-1} + b_o) \tag{3}$$

$$C^t = G_f^t \times C^{t-1} + G_f^t \times \tanh\,(W_c x^t + U_c h^{t-1} + b_c) \tag{4}$$

$$h^t = G_o^t \times \tanh\,(C^t) \tag{5}$$

U and W denote the weight matrices of each gate, while the bias is provided by b. The activation functions are σ and tanh. The figure 3 and 4 shows the diagram of Bi-LSTM and RNN.

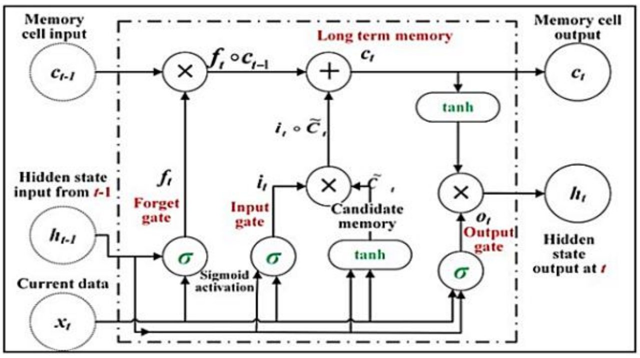

Figure 3: A LSTM network[24,25].

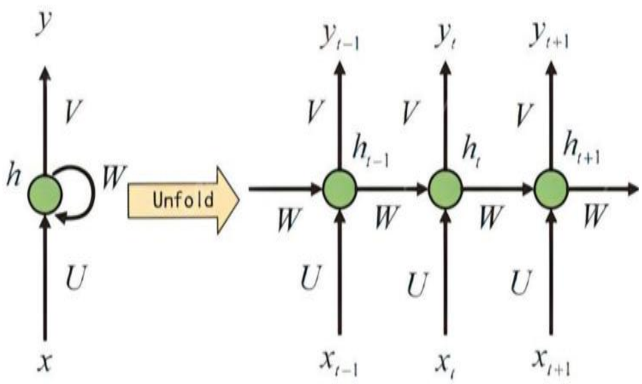

Figure 4: A representation of the RNN paradigm[26].

Evaluation Matrix

The recognition and moderation strategy, which is based on the classification methods, was assessed using a set of evaluation metrics to establish the efficacy and resilience of the models. The Accuracy, Precision, recall, and F1-measure were some of the performance indicators that were included in the evaluation. In Table 2, they can see how well a classification model performed after we built it up and connected the predicted and actual class data. Table 3 is called the confusion matrix. It is comprised of four core variables that are used in the computation of the performance metrics that were previously discussed. They are defined as follows: The evaluation matrix is [27-29]: The proportion of correct observations to the total number of observations is known as accuracy. One way to determine it is by using

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

A positive predictive value, or precision, is calculated as the proportion of accurate positive sample observations to the total number of positive observations. Here is the calculation using equation (6).

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Table 2: Confusion Matrix

Actual Class	Ture Outcomes	
	Positive	Negative
Ture	TP	FP
False	FN	TN

The percentage of positive observations that were correctly predicted relative to the total number of observations in the real class is called recall. The accuracy with which the classifier anticipates the true positive class is represented by its precision, as seen in Equation (7).

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

A weighted average of recall and accuracy is known as F1-Measure. Here is the calculation using equation (8).

$$F1 - score = \frac{2*Precision*Recall}{Precision+Recall} \quad (9)$$

An FPR, also known as specificity, is the percentage of true positives relative to the total number of false positives that were incorrectly identified as assaults. According to equation (9), it is possible to determine.

$$FPR = \frac{FP}{TN+FP} \quad (10)$$

The TPR is the likelihood that a sample would come back positive. The specificity or true negative rate, which is the likelihood that a real negative would be detected by a test.

$$TPR = \frac{TP}{TP+FN} \quad (11)$$

The RNN-Bi-LSTM hybrid classifier that was suggested has been demonstrated to operate better than other RNN and LSTM approaches, based to the findings of tests that were carried out on a total of various datasets. A few of the most important things that researchers conduct include the investigation of performance indicators like as accuracy, precision, recall, and F1-score for illustration. An important component of the explanation of results is the study of these metrics and the computation of the percentage of advancement that the suggested strategy delivers in contrast to the RNN and LSTM technique that are already in use.In terms of accuracy, the RNN-Bi-LSTM technique is superior to both RNN and LSTM in terms of its ability to accurately predict each epoch. The accuracy of the suggested technique is 85.5% when compared to that of RNN at epoch 50. In a manner comparable to that of LSTM at 40 epochs, the suggested approach has an accuracy of 86.5%. Because it more truly represents the complexity that are included within the datasets, the hybrid technique is better to the other methods when it comes to recognizing ADRs. A graph showing the accuracy at 100 epochs is shown in the figure 5. A classifier's ability to distinguish acceptable instances is evaluated by the accuracy metric, which then assigns a score depending on the results of this evaluation. The strategies that were suggested demonstrated that the value of accuracy is higher than that of the RNN and LSTM methods at each epoch. When contrasted with RNN at epoch 70, the suggested technique has a recall rate of 92.48%. In a manner comparable to that of LSTM at 50 epochs, the suggested technique has a recall rate of 91%.

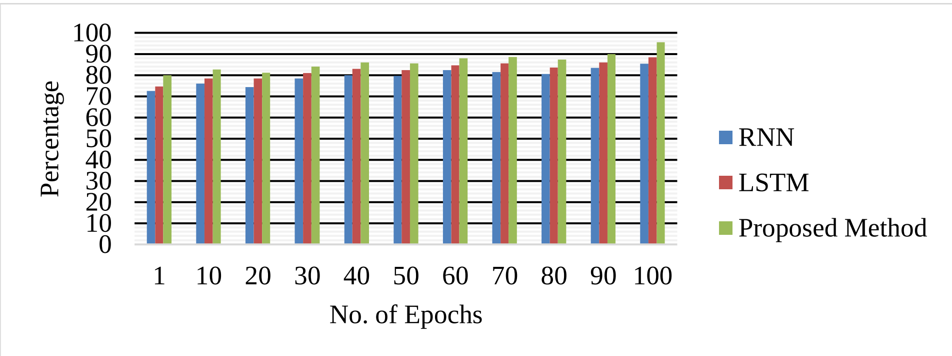

Figure 5: Accuracy

Based on the data that is currently available, it has been shown that the hybrid classifier has the ability to reduce false positives in a more efficient manner, which eventually leads to improved accuracy in the identification of ADR. Figure 6 shows the graph of precision. The ability to recall, which is often referred to as sensitivity, is a technique that can be used to evaluate an individual's capacity to remember every positive event. A recall rate of 90% is achieved by the suggested technique when compared to RNN at epoch 70. At 50 epochs, the suggested technique has a recall rate of 89%, which is comparable to that of LSTM method. It is possible to draw the conclusion that the Bi-LSTM-RNN technique is better in terms of its capacity to discover real positive instances, which ultimately increases the recall in ARD. There is a graph of recall shown in the figure 7.

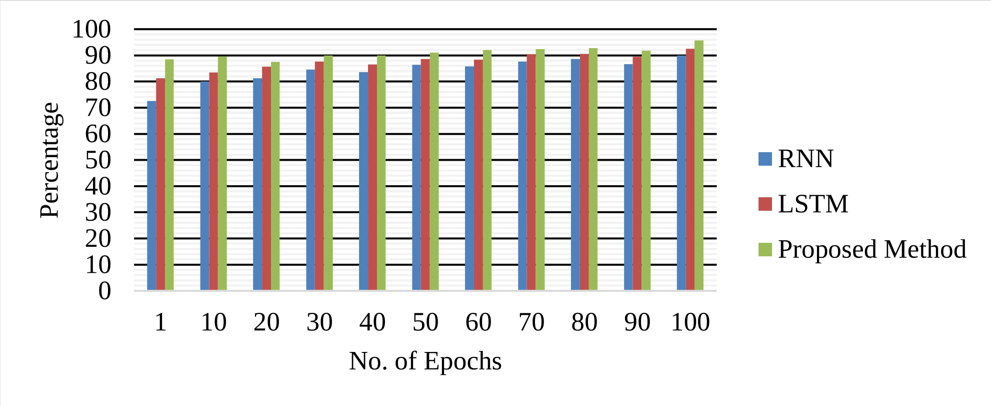

Figure 6: Precision

A realistic evaluation of the effectiveness of a classifier can be obtained via the use of the F1-score, which takes into account both the precision and the recall of the classifier. At epoch 50, the suggested technique has an F1-score of 84.5%, which is higher than that using RNN. The suggested technique has an F1-score of 84%, which is comparable to that of LSTM at 40 epochs. The effectiveness of the hybrid technique in achieving a balance between accuracy and recall is shown by this instance. The below graph depicts the F1-score at 100 epochs, as seen in the figure 8.

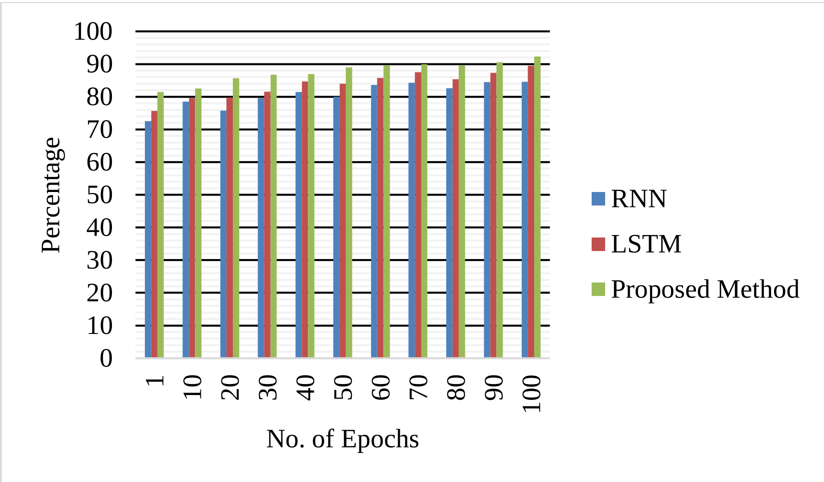

Figure 7: Recall

They provide a comparison between the work that has been done in the past and the present. The accuracy value of prior study work is shown in the table 3, and the graph of comparison analysis based on accuracy is displayed graphically in the figure 9. The graph demonstrates that the strategy performed far better than the preceding study by a substantial margin. For example, method [30] has an accuracy of 94.44, method [31] has an accuracy of 70.34, method [32] has an accuracy of 94.29, and so on. An accuracy of 95.6 is achieved by our work.

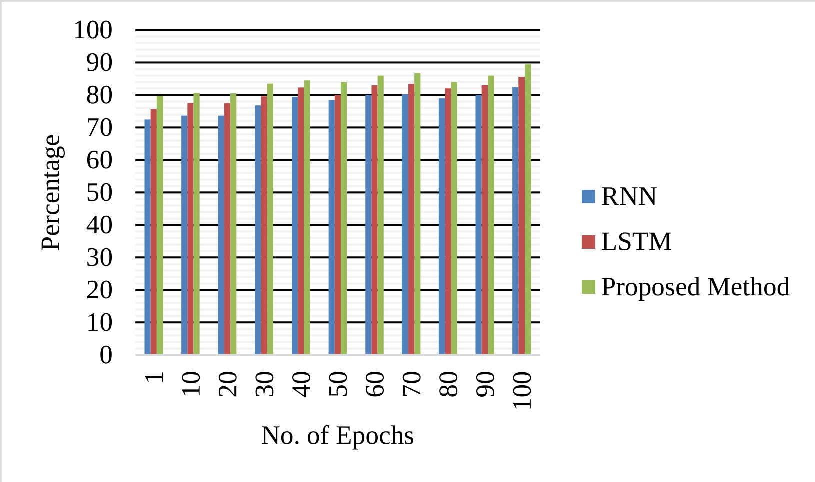

Figure 8: F1-score

Table 3: Comparison analysis of previous work

Reference	Methods	Dataset	Accuracy (%)
[30]	SVM	DS	94.44
[31]	Adversarial transfer learning	Twi-Med	70.34
[32]	NB	CADEC	94.29
[33]	Cascade feature extraction and meta-learner (CFEML)	ADR	85.52
[34]	Deep linguistic features	Daily-Strength	94.44
This work	Proposed method	CADEC	95.6

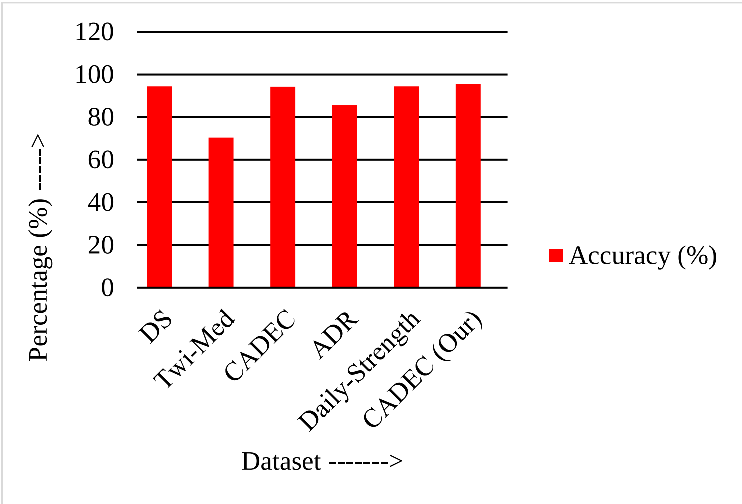

Figure 9: Graph of comparative analysis

CONCLUSION

ADRs present significant challenges in healthcare due to their potential to cause harm and adverse outcomes in patients. Traditional methods of ADR detection rely heavily on spontaneous reporting systems and clinical trials, which often suffer from underreporting and delayed recognition of adverse events. To address these limitations, this study proposes a novel method utilizing social media data for enhanced ADR detection.This research explores the development and implementation of a Hybrid Classifier Model (RNN-Bi-LSTM) for optimal ADR detection using social media data. The study used a versatile dataset that was assembled from many sources, including records from the Clinical Pharmacy Department, PubMed, and online message boards. To extract nuanced patterns and context from structured and unstructured data, the suggested approach employs state-of-the-art feature extraction methods as Word Net, TF-IDF, Semantic Similarity, Higher Order Statistical Features, and Sentiment Analysis. The outcomes show that the hybrid classifier outperforms the standard approaches in terms of recall, F1-score, and accuracy. According to the results of the experiments, the RNN-Bi-LSTM approach obtains the maximum accuracy of 95.6%.

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