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Original Article

Spotted Hyena Optimization with Deep Learning-Based Automatic Text Document Summarization Model

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Abstract - *Automatic text summarization is an active investigation region determined as removing snippets or introductory sentences of a massive document and relating them as a short form of documents. Text Summarization can be either cost-efficient or time-efficient. An abstractive or extractive summary was studied with distinct algorithms comprising deep learning (DL), graph, and statistical-based techniques. DL has attained promising shows in comparison to the typical methods. With the development of various neural structures like the attention mechanism (usually called a transformer), there is a potential growth area for summarization tasks. Hence, this research presents a Spotted Hyena Optimization with Deep Learning based Automatic Text Summarization (SHODL-ATS) model. The SHODL-ATS technique's principal objective lies in the documents' automated summarization. To accomplish this, the presented SHODL-ATS technique performs data preprocessing to convert the data into a convenient form. The SHODL-ATS technique uses an Attention-based Bidirectional Gated Recurrent Unit (ABiGRU) model for summarizing the text documents. Finally, the SHO technique is enforced for the parameter tuning of the ABiGRU approach. To examine the achievement of the SHODL-ATS model, we validate the outcomes on benchmark datasets. The results indicate the promising achievement of the SHODL-ATS method over other existing techniques.*

Keywords - *Text summarization, Spotted Hyena optimizer, Deep learning, Natural language processing.*

1. Introduction

Lately, there has been a massive volume of textual data, including reviews, online files, news, and articles with long strings of texting that must be summarized [1]. Text summarization gains significance for various reasons, including resolving the issues linked with criteria required for evaluating summary [2], retrieving essential data from long textual data in a brief time, and easy and swift rendering of the crucial data. Owing to the development and evolution of automatic text summarizing models [3], which have offered outcomes in numerous languages, such techniques should be reviewed and summarised. Hence, this study surveyed the current methods and concentrated on the approaches [4], the difficulties of all models, datasets, and evaluation measures, and how these techniques overcome the obstacles [5].

Applications, namely news websites and search engines, utilize textual summarization [6]. In the search engines, previews were made as snippets, and news websites made captions to explain news for retrieving knowledge [7]. A number of documents, functions, types of summarizers, genres, and summary contexts are various categories of text summarisation [8]; one text summarisation classifier technique divided the summarisation process into extractive and abstractive classes [9]. However, the TS methods have reached significant consequences in several recognized datasets, and such methods unsolved all the issues [10].

Syntactic and Semantics structure were two substantial elements to assess the TS method [11], but these two models focused on just one factor alone. The gain of ETS methods is that the sentence, in summary, should comply with the needs of syntactic structure [12]. However, the demerit of ETS techniques is that sentences may not be semantically transparent. It is considered a demerit because the adjacent sentences in summaries are not adjacent in the original texts [13].

The present ATS methods are optimally grained and method summaries with semantic matters (phrases, words, etc.) [14]. The benefit of ATS methods is inclusive semantics since such approaches learn the comparison among words and generate a series of keywords depending on the association among words after training. Rare words are the other main issue of mainstream ATS methods [15]. The prominence of rare words can be determined by the collocation of the words and the number of occurrences.

However, humans will employ more components to decide whether a word is significant [16]. A few words that hardly appear are unimportant, but a part of the words is vital for constructing a summary from a human's view. This study presents a Spotted Hyena Optimization with Deep Learning based Automatic Text Summarization (SHODL-ATS) model. The SHODL-ATS technique's principal aim lies in the documents' automated summarization. To accomplish this, the presented SHODL-ATS technique performs data preprocessing to convert the data into a convenient form. The SHODL-ATS technique summarises the text documents using an Attention-based Bidirectional Gated Recurrent Unit (ABiGRU) model. At last, the SHO technique is enforced for the tuning process of the ABiGRU. To examine the achievement of the SHODL-ATS approach, we validate the outcomes on benchmark datasets.

2. Related Works

Nafees Muneera and Sriramya [17] designed a fusion feature excerption among the Multi-layered attentional StackedLSTM (MASta-LSTM-RNN) in addition to the Attention RNN networks that routinely generate a summarization of prolonged texting. In the presented method, an input of the association between the class and word, the StackedLSTM module, was displayed by a distinct vector as inputs of the MLP model for acquiring exhaustive learning of time-series attribute data, the relationship amongst classes and words of news text and spatial attribute data.

Song et al. [18] devised an LSTM-CNN-related ATS structure (ATSDL) that can create novel sentencing by further discovering optimally grained segments than sentencing. Unlike the current extraction-related methods, ATSDL contains two key phases, the initial one abstracts phrases from the source sentence, and the next produces text summarizations using DL. Liang et al. [19] devised a selectively reinforced sequence-to-sequence attention mechanism to summarise social media text. The author added selective gate afterwards encoder modules to filter invalid data better. To be Specific, the author devises the cross-entropy and RL to boost the ROUGE score by directly combining policy.

Yang et al. [20, 21] offer a new Hierarchical Human-like DNN for ATS (HH-ATS), enthused by the procedure of how human beings understand and write the respective summarization of an article. In particular, HH-ATS contains three principal elements, which mimic active reading, post-editing, and grim reading. Kouris et al. [22, 23] introduced a new structure combining DL approaches and semantic data conversion for enhancing abstractive text summarization. At first, a theoretical method for semantic-related text generalization was presented and utilized with a deep encoder-decoder structure for producing a summary in a generalized format.

Jang and Kim's [22], the author's main objective is to increase the summarization quality statement by devising a rewarding function in textual summary related to RL. In contrast to ROUGE-L, ROUGE-SIM enable meaningful word. The semantic similarities among summary text and articles were calculated by implementing Word Mover's Distance approach.

3. The Proposed Model

In this study, we have presented a new SHODL-ATS technique for the summarization of documents. The aim of the SHODL-ATS technique lies in the automated summation of the documents. The presented SHODL-ATS technique involves preprocessing, ABiGRU-based summarization, and SHO-based tuning procedure to accomplish this. Figure 1 signifies the overall flow of the SHODL-ATS model.

3.1. Preprocessing

Firstly, the suggested SHODL-ATS method achieves preprocessing for converting the information into a convenient form. The fundamental model generates the input textual documentation for processing in additional phases [26, 27]. It broadcasts the input document as essential data. The projected algorithm comprises preprocessed sequenced functions like tokenization, stemming, letter normalization, and elimination of stop-wordings.

At the time of extraction feature, sentences of high importance are selected from the feature grouping that contains a coherent summarization representing the critical problem of available documentation. An input document that is preprocessed can be suggested as the feature vector. These elements can be utilized to signify summary sentences.

3.2. Summarization using ABiGRU Model

For summarizing the text documents, the SHODL-ATS technique applied the ABiGRU model. GRU technique retains the LSTM actual result with numerous parameters, more accessible infrastructure, an optimal convergence process, etc. It comprises reset and update gates [28, 29].

The update gate determines the limitation to which the prior output Hidden Layer (HL) will affect the current layer. The more excellent value is, the more substantial impact is. The reset gate describes that the previous data of the hidden state has been disregarded:

$$r_n = \sigma(W_r * [h_{n-1}, x_n]) \tag{1}$$

$$z_n = \sigma(W_z * [h_{n-1'} x]) \tag{2}$$

$$\tilde{h}_n = \tanh(W_{\tilde{h}} * [r_n * h_{n-1}, x_n]) \tag{3}$$

$$h_n = (1 - z_n) * h_{\mathrm{n}-1} + z_n * \tilde{h}_n \tag{4}$$

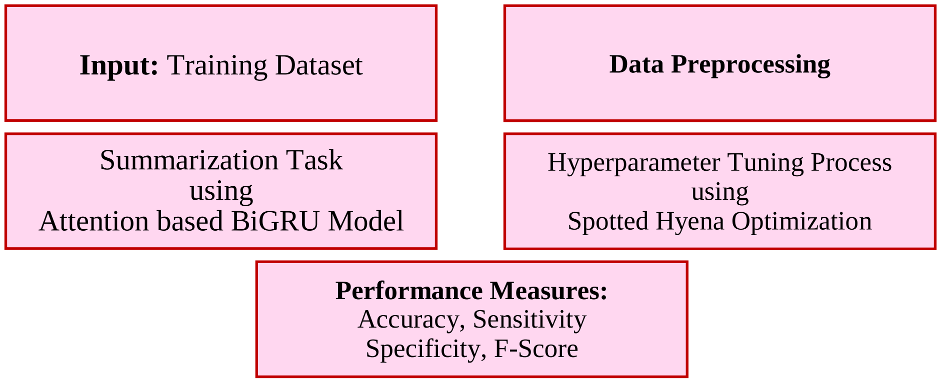

Fig. 1 Overall flow of the SHODL-ATS system

Where, Z_n denotes the update gate at the time $\tilde{h}$, h_{n-1} determines the activation state at n time, r_n characterizes the reset gate at n time, h_{n-1} indicates the hidden state at $(n-1)$ time, and h_n denotes the active candidate layer at n time. The z update gate has determined, as the past dataset, that the current state needs. to be forgotten and a novel dataset; the reset gate r has determined as the dataset accomplished in the past dataset of the candidate state. To perform at every moment, the input provides 2 GRUs in a contradictory manner, and the output can be determined as two uni-directional GRUs.

The present HL of BiGRU has illustrated the collection of output. $\overleftarrow{h}_{n-1}$ of HL forwarded at x_i and $(n-1)$ moment and the contrary HL $\overleftarrow{h}_{n-1}$. BiGRU is split into two uni-directional GRU, thereby HL. $\vec{h}_{n-1}$ of BiGRU at n timing has been obtained by the reverse HL $\overleftarrow{h}_{n-1}$ weighting and forwarded HL:

$$\vec{h}_n = GRU\left(x_{n'}\vec{h}_{n-1}\right) \tag{5}$$

$$\overleftarrow{h}_n = GRU\left(x_{n'}\overleftarrow{h}_{n-1}\right) \tag{6}$$

$$h_n = w_n\vec{h}_n + v_n\overleftarrow{h}_n + b_n \tag{7}$$

Where w_n and v_n Indicate the weighted corresponding to $\vec{h}_n$ forwarded HL state and $\overleftarrow{h}_n$, contrary HL state corresponding to BiGRU at n time; the $GRU()$ function represents the nonlinear variation to input word vector. b_n determines the offset value corresponding to the HL state at n time. This work adds attention mechanisms to the BiGRU method that aims to define adaptive weight based on the likelihood distribution [30, 31], and it is formulated as follows:

$$e_i = \chi_a^T \tanh\left(\omega_a h_i + b\right), \tag{8}$$

In Eq. (8), b signifies the offset vector, h_i denotes the output of the HL, ω_a shows the arbitrary initiation weight matrix, and χ_a represents the arbitrary initiation vector. Next, the weight score θ is defined as follows:

$$\theta = \frac{\exp(e_i)}{\sum_{k=1}^{L}\exp(e_i k)} \tag{9}$$

Therefore, the output vector c_i weighted by the adaptive weight is represented as follows:

$$c_i = \sum_{j=1}^{L}\theta\cdot h_j \tag{10}$$

Later, the softmax function is applied to standardise the likelihood dispersion.

3.3. Hyperparameter Tuning using SHO Algorithm

In the last phase, the SHO approach is enforced for the tuning process of the ABiGRU technique. The fundamental notion of SHO was first introduced before the multiobjective variants of SHO were recommended [30, 31]. Spotted hyenas' hunting habits and social interactions were the primary motivation for the presented method. The SHO mimics the SH coherent group. The four critical components of SHO are surrounding, Searching, attacking, and hunting. The following equation is utilized for modelling the circling pattern of spotted hyena:

$$D_h = \left|\vec{B}\cdot\overrightarrow{X_p}(x) - \vec{X}(x)\right| \tag{11}$$

$$\vec{X}(x+1) = \vec{X}_p(x) - \vec{E}\cdot\vec{D}_h \tag{12}$$

Where $\vec{D}_h$ denotes the separation between the SH and the target, χ denotes the iteration, $\vec{X}_p$ and X indicate the location vector of the SH and its target. Correspondingly, || represents the absolute value, and $\vec{B}$ and $\vec{E}$ denote the coefficient vectors. The formula used for evaluating $\vec{B}$ and $\vec{E}$ is given below:

$$\vec{B} = 2 \cdot r\vec{d}_1 \tag{13}$$

$$\vec{E} = 2\vec{h} \cdot r\vec{d}_2 - \vec{h} \tag{14}$$

$$\vec{h} = 5 - \left(Iteration \times \frac{5}{\text{Max}_{iteration}}\right) \tag{15}$$

In Eq. (15), iteration $is_{\rightarrow}$between 1 to maximum iteration.

In such cases, h shows $gradual \rightarrow$ minimisation throughout iteration from 5 to 0. The stochastic arrays rd_1 and $r\vec{d}_2$ range from zero to one. By altering the value of vectors $\vec{B}$ and $\vec{E}$, other locations are accomplished based on the current position.

This process pushed other search agents to enhance the location while storing the optimum solution. The following equation was generated for replicating the hunting behaviours of SH and recognizing the possible random search area:

$$\vec{D} = \left|\vec{B} \cdot \vec{X}_h - \overrightarrow{X_k}\right| \tag{16}$$

$$\vec{X}_k = \overrightarrow{X_h} - \vec{E} \cdot \overrightarrow{D_h} \tag{17}$$

$$\overrightarrow{C_h} = \overrightarrow{X_k} + \overrightarrow{X_k} + \cdots + \overrightarrow{X_{k+N}} \tag{18}$$

Where N denotes the number of iterations, that is evaluated as follows:

$$N = count_{nos}\left(\vec{X}_k + \vec{X}_{h+1} + \vec{X}_{h+2}, \dots \dots, \vec{X}_{k+M}\right) \tag{19}$$

$$\vec{X}_{(x+1)} \frac{\vec{C}_h}{N} \tag{20}$$

Where nos indicates the number of potential solutions that are the same as the optimal solution, $\vec{C}_h$ represents a cluster or collection of optimum resolutions, and $\vec{M}$ represents a random vector within 0.5 and 1. $\vec{X}_{(x+1)}$ modifies the location of the searching agent according to the position of the effective algorithm completion and stores the N optimal solution. Figure 2 represents the SHO model flowchart.

The search candidate needed to retreat from the target by the exploring condition attained via vector. $\vec{E}$ with a random value more excellent or lesser than one. $\vec{B}$, an additional SHO component, is responsible for exploring. If $|\vec{E}| < 1$, the SHO process attacks the prey by meeting the prey's evaluated position. However, during repetitions $\vec{h}$ and $\vec{E}$, vectors continuously decline. Once the hiring condition is reached, the placement of a candidate solution that forms a cluster is considered the optimal solution.

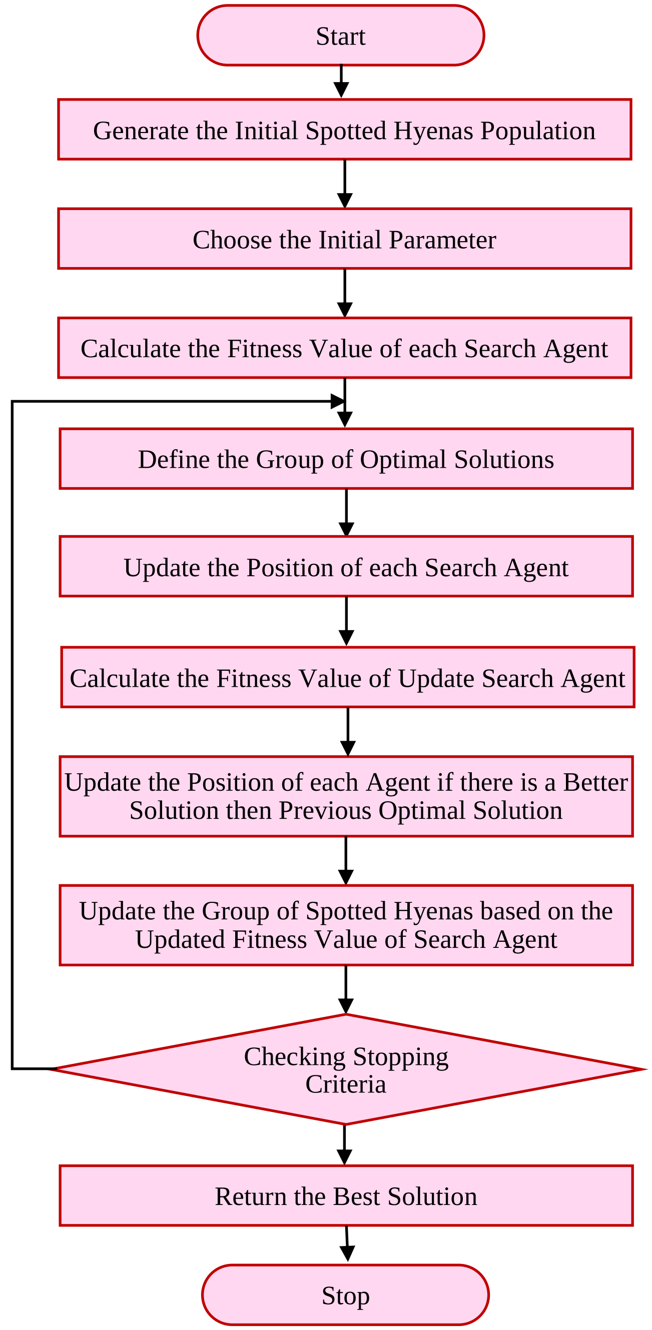

Fig. 2 Flowchart of SHO

The SHO method can be able to resolve optimization issues efficiently. The massive exploration capability produces superior outcomes than the existing metaheuristics. Consequently, SHO's solutions do not become locked-in optimum solutions.

4. Results and Discussion

The ATS outcomes of the SHODL-ATS technique are tested on the Document Understanding Conferences (DUC) Dataset.

Table 1. Comparative result of SHODL-ATS algorithm under a single document

Single Document					
File Size (Kb)	**SHODL-ATS**	**DL-MNN Model**	**ANN Model**	**RF Model**	**SVM Model**
Sensitivity					
1000	85.49	84.99	83.52	81.67	78.90
2000	90.17	87.02	85.19	82.65	82.46
3000	94.57	92.00	90.17	88.07	85.05
4000	96.13	94.02	93.58	91.75	88.30
5000	99.16	97.23	95.77	94.94	91.29
Specificity					
1000	85.83	82.84	82.61	80.86	77.14
2000	90.14	85.44	82.88	81.74	81.18
3000	91.42	88.10	86.69	86.18	83.15
4000	93.78	91.68	91.13	89.91	88.41
5000	94.90	92.29	92.11	89.80	87.87
Accuracy					
1000	89.28	84.94	81.12	79.47	78.18
2000	90.94	89.10	85.38	84.97	83.30
3000	92.18	91.46	88.60	88.91	86.51
4000	94.52	92.15	91.26	88.44	86.50
5000	99.55	94.68	91.05	89.80	88.00
F-Score					
1000	89.60	85.83	81.42	82.75	79.81
2000	91.26	87.31	84.17	84.17	81.39
3000	91.60	88.24	88.93	86.73	84.56
4000	96.46	94.13	90.82	89.04	86.65
5000	99.00	94.01	93.44	91.86	90.36

Table 1 and Figure 3 represent comparative outcomes of the SHODL-ATS model on a single document with varying file sizes [26, 27]. The results indicate that the SHODL-ATS technique reaches improved results under all file sizes.

Based on $sens_y$ with 1000kb file, the SHODL-ATS technique reaches a higher $sens_y$ of 85.49%, while the DL-MNN, ANN, RF, and SVM models obtain lower $sens_y$ of 84.99%, 83.52%, 81.67%, and 78.90% respectively. Meanwhile, with a 3000kb file, the SHODL-ATS algorithm obtains a superior $sens_y$ of 94.57%, while the DL-MNN, ANN, RF, and SVM algorithms gain lesser $sens_y$ of 92%, 90.17%, 88.07%, and 85.05% correspondingly. Moreover, with a 5000kb file, the SHODL-ATS methodology gains a superior $sens_y$ of 99.16% while the DL-MNN, ANN, RF, and SVM algorithms reach reduced $sens_y$ of 97.23%, 95.77%, 94.94%, and 91.29% correspondingly.

With respect to $spec_y$ with 1000kb file, the SHODL-ATS algorithm gains improved $spec_y$ of 85.83% while the DL-MNN, ANN, RF, and SVM models achieve reduced $spec_y$ of 82.84%, 82.61%, 80.86%, and 77.14% correspondingly. In the meantime, with a 3000kb file, the

SHODL-ATS technique reaches a higher $spec_y$ of 91.42% while the DL-MNN, ANN, RF, and SVM systems reach a decrease $spec_y$ of 88.10%, 86.69%, 86.18%, and 83.15% correspondingly. In addition, with a 5000kb file, the SHODL-ATS methodology gains an improved $spec_y$ of 94.90% while the DL-MNN, ANN, RF, and SVM systems attain reduced $spec_y$ of 92.29%, 92.11%, 89.80%, and 87.87% correspondingly.

Interms of $accu_y$ with 1000kb file, the SHODL-ATS algorithm attains improved $accu_y$ of 89.28% while the DL-MNN, ANN, RF, and SVM systems obtain least $accu_y$ of 84.94%, 81.12%, 79.47%, and 78.18% correspondingly. Likewise, with a 3000kb file, the SHODL-ATS technique reaches a higher $accu_y$ of 92.18% while the DL-MNN, ANN, RF, and SVM models obtain lower $accu_y$ of 91.46%, 88.60%, 88.91%, and 86.51% correspondingly. Eventually, with a 5000kb file, the SHODL-ATS system reaches an improved $accu_y$ of 99.55% while the DL-MNN, ANN, RF, and SVM algorithms attain reduced $accu_y$ of 94.68%, 91.05%, 89.80%, and 88% correspondingly.

For F_{score} with a 1000kb file, the SHODL-ATS algorithm gains an enhanced F_{score} of 89.60% while the DL-MNN, ANN, RF, and SVM techniques gain a reduced F_{score} of 85.83%, 81.42%, 82.75%, and 79.81% correspondingly. In addition, with a 3000kb file, the SHODL-ATS approach achieves an improved F_{score} of 91.60% while the DL-MNN, ANN, RF, and SVM algorithms gain lesser F_{score} of 88.24%, 88.93%, 86.73%, and 84.56% correspondingly. Additionally, with a 5000kb file, the SHODL-ATS technique reaches a superior F_{score} of 99% while the DL-MNN, ANN, RF, and SVM algorithms reach a lesser F_{score} of 94.01%, 93.44%, 91.86%, and 90.36% correspondingly.

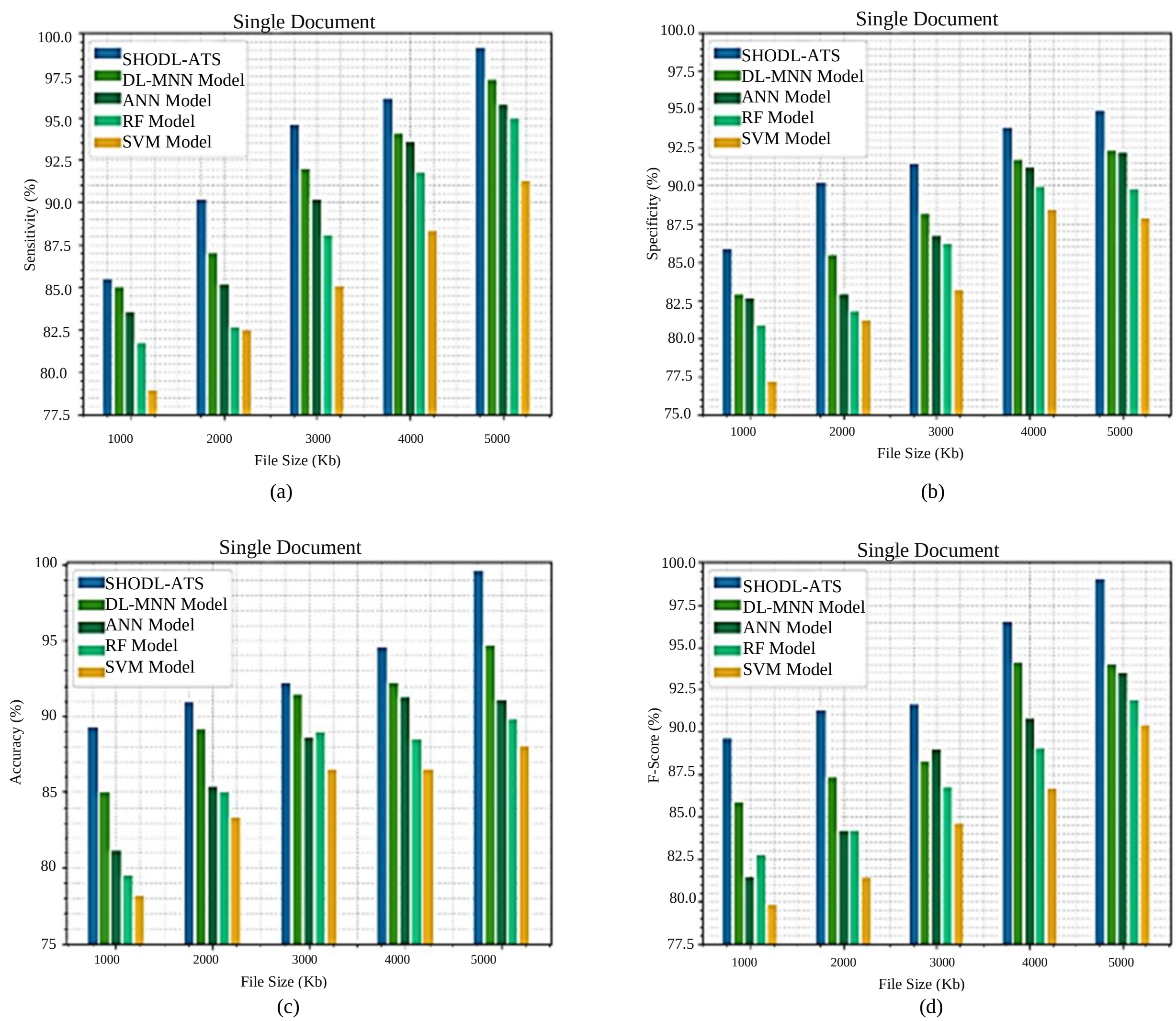

Fig. 3 Comparative result of SHODL-ATS system under single document (a) $Sens_y$, (b) $Spec_y$, $Accu_y$, and (d) F_{score}

Table 2. Comparative result of SHODL-ATS algorithm under a multi document

Multi Document					
File Size (Kb)	**SHODL-ATS**	**DL-MNN Model**	**ANN Model**	**RF Model**	**SVM Model**
Sensitivity					
1000	86.91	85.07	81.61	80.32	78.72
2000	89.78	87.89	85.80	83.02	80.15
3000	90.94	87.92	88.76	86.75	84.49
4000	96.63	92.55	89.87	88.97	87.38
5000	98.74	94.81	93.92	90.48	87.87
Specificity					
1000	87.22	83.45	82.68	81.16	79.61
2000	88.07	85.95	82.55	81.17	78.07
3000	89.06	88.23	84.65	82.57	80.73
4000	91.83	86.17	85.16	84.07	82.47
5000	95.77	89.33	89.55	84.93	84.22
Accuracy					
1000	87.94	85.17	82.35	82.84	79.58
2000	92.21	87.44	87.58	85.31	82.96
3000	95.32	92.18	89.01	87.30	85.79
4000	97.11	94.21	92.33	88.46	88.23
5000	97.56	96.33	95.30	93.02	89.46
F-Score					
1000	88.66	86.02	80.79	79.06	79.22
2000	92.15	86.60	87.94	85.48	83.16
3000	92.70	90.76	88.54	88.48	86.50
4000	96.11	95.48	93.08	90.96	90.45
5000	98.74	97.47	95.94	96.33	92.12

The TACY and VACY of the SHODL-ATS algorithm under single documentation are defined in Figure 4. The figure denoted that the SHODL-ATS technique has depicted higher results with maximal TACY and VACY values. Note that the SHODL-ATS approach has reached maximal TACY outputs. The TLOS and VLOS values of the SHODL-ATS system under single documentation are defined in Figure 5. The figure demonstrated that the SHODL-ATS algorithm had illustrated an improved achievement with the minimum TLOS and VLOS values. Note that the SHODL-ATS technique has given an outcome in minimum VLOS outputs.

Table 2 and Figure 6 signify comparative outcomes of the SHODL-ATS algorithm on a multi-document with varying file sizes [27]. The outcomes referred that the SHODL-ATS technique gains enhanced outcomes under all file sizes. With respect to $sens_y$ with 1000kb file, the SHODL-ATS technique reaches a higher $sens_y$ of 86.91% while the DL-MNN, ANN, RF, and SVM approaches acquire minimal $sens_y$ of 85.07%, 81.61%, 80.32%, and 78.72% correspondingly.

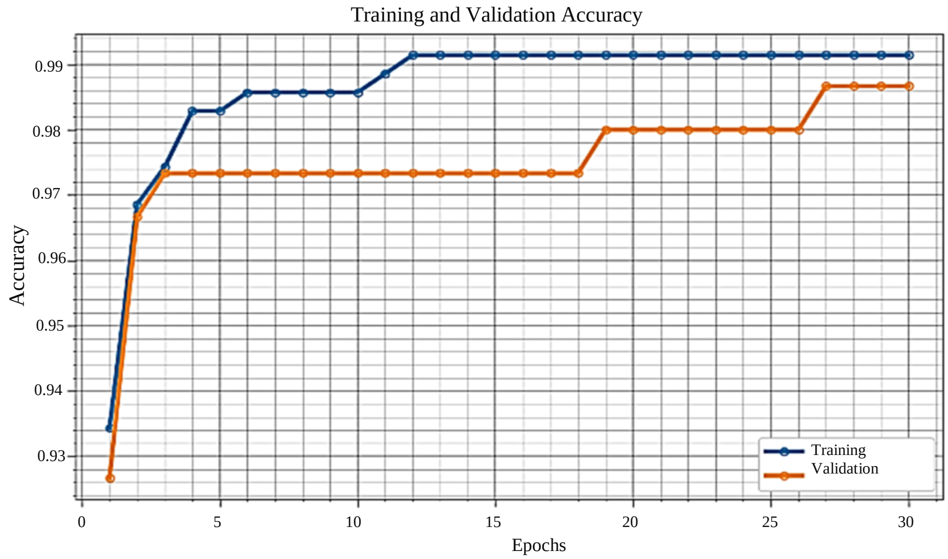

Fig. 4 TACY and VACY result of SHODL-ATS system under a single document

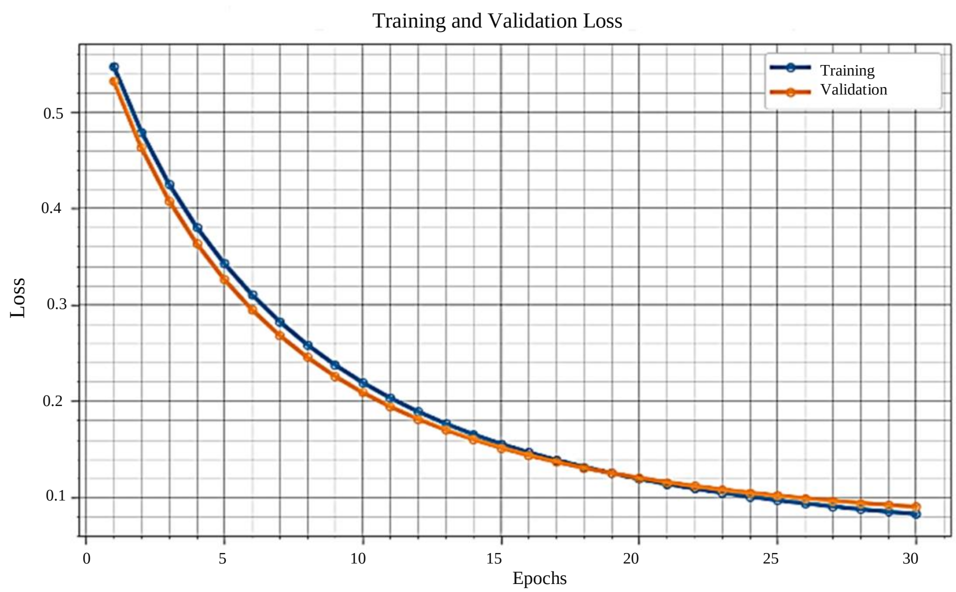

Fig. 5 TLOS and VLOS result of SHODL-ATS system under a single document

In the meantime, with a 3000kb file, the SHODL-ATS technique reaches an improved $sens_y$ of 90.94% while the DL-MNN, ANN, RF, and SVM systems reach a lesser $sens_y$ of 87.92%, 88.76%, 86.75%, and 84.49% correspondingly. Besides, with a 5000kb file, the SHODL-ATS algorithm reaches a greater $sens_y$ of 98.74% while the DL-MNN, ANN, RF, and SVM techniques attain lesser $sens_y$ of 94.81%, 93.92%, 90.48%, and 87.87% correspondingly.

Based on $spec_y$ with 1000kb file, the SHODL-ATS technique reaches a higher $spec_y$ of 87.22% while the DL-MNN, ANN, RF, and SVM models obtain lower $spec_y$ of 83.45%, 82.68%, 81.16%, and 79.61% respectively. Meanwhile, with a 3000kb file, the SHODL-ATS technique reaches a higher $spec_y$ of 89.06% while the DL-MNN, ANN, RF, and SVM models obtain lower $spec_y$ of 88.23%, 84.65%, 82.57%, and 80.73% respectively. Moreover, with a 5000kb file, the SHODL-ATS technique reaches a higher $spec_y$ of 95.77% while the DL-MNN, ANN, RF, and SVM models obtain lower $spec_y$ of 89.33%, 89.55%, 84.93%, and 84.22% respectively.

With respect to $accu_y$ with 1000kb file, the SHODL-ATS algorithm gains superior $accu_y$ of 87.94% while the DL-MNN, ANN, RF, and SVM methods obtain lower $accu_y$ of 85.17%, 82.35%, 82.84%, and 79.58% correspondingly.

Besides, with a 3000kb file, the SHODL-ATS system reaches an improved $accu_y$ of 95.32% while the DL-MNN, ANN, RF, and SVM models obtain decreased $accu_y$ of 92.18%, 89.01%, 87.30%, and 85.79% respectively. Finally, with a 5000kb file, the SHODL-ATS technique reaches an enhanced $accu_y$ of 97.56% while the DL-MNN, ANN, RF, and SVM algorithms reach lower $accu_y$ of 96.33%, 95.30%, 93.02%, and 89.46% correspondingly.

Interms of F_{score} with 1000kb file, the SHODL-ATS method reaches a higher F_{score} of 88.66% while the DL-MNN, ANN, RF, and SVM systems attain reduced F_{score} of 86.02%, 80.79%, 79.06%, and 79.22% respectively. In addition, with a 3000kb file, the SHODL-ATS method reaches a higher F_{score} of 92.70% while the DL-MNN, ANN, RF, and SVM approaches obtained lesser F_{score} of 90.76%, 88.54%, 88.48%, and 86.50% correspondingly. Eventually, with a 5000kb file, the SHODL-ATS technique reaches a higher F_{score} of 98.74% while the DL-MNN, ANN, RF, and SVM algorithms gain lesser F_{score} of 97.47%, 95.94%, 96.33%, and 92.12% correspondingly.

The TACY and VACY values of the SHODL-ATS algorithm under multi-document are represented in Figure 7. The figure specified that the SHODL-ATS algorithm had improved performance with improved TACY and VACY values. It can be clear that the SHODL-ATS model has reached maximal TACY outputs.

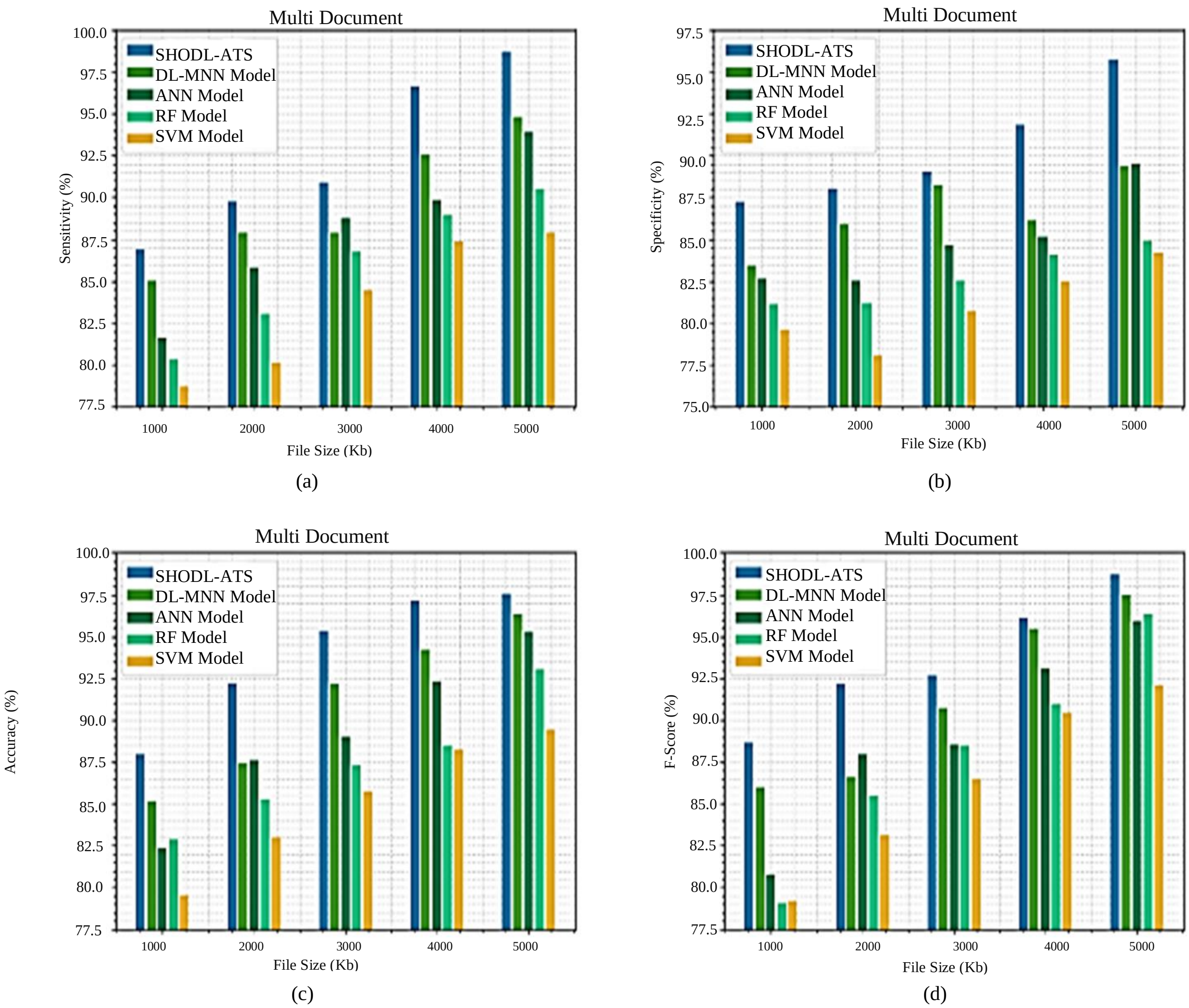

Fig. 6 Comparative result of SHODL-ATS system under multi document (a) $Sens_y$, (b) $Spec_y$, $Accu_y$, and (d) F_{score}

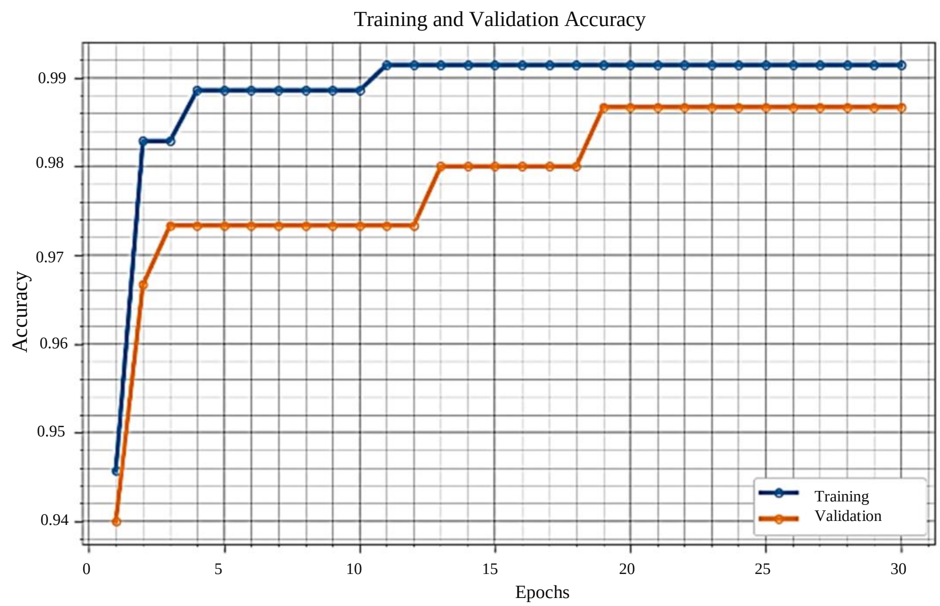

Fig. 7 TACY and VACY result of SHODL-ATS system under a multi document

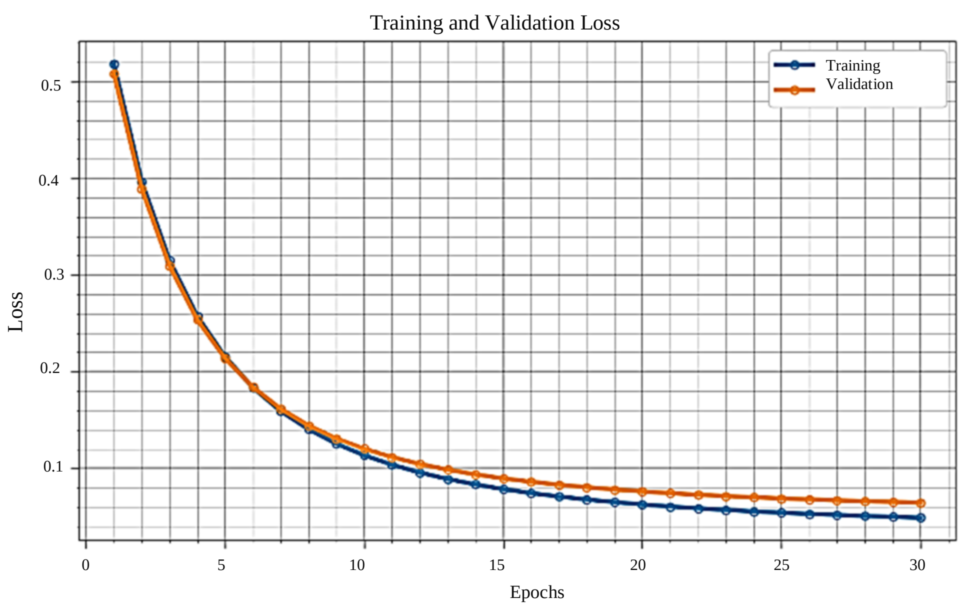

Fig. 8 TLOS and VLOS result of SHODL-ATS system under a multi document

The TLOS and VLOS values of the SHODL-ATS algorithm under multi-document are signified in Figure 8. The figure inferred that the SHODL-ATS algorithm had revealed the best result with the minimum TLOS and VLOS values. It can be noticeable that the SHODL-ATS model has given an outcome in minimum VLOS outputs.

5. Conclusion

In this research, we have presented a new SHODL-ATS model for the summarization of documents. The aim of the SHODL-ATS model lies in the automated summarization of the documents. To accomplish this, the presented SHODL-ATS technique performs data preprocessing to convert the information into a convenient system. For summarizing the text documents, the SHODL-ATS technique applied the ABiGRU approach. Finally, the SHO approach is used for the parameter tuning of the ABiGRU approach. To examine the performance of the SHODL-ATS approach, we validate the results on benchmark datasets. The results indicate the promising performance of the SHODL-ATS method over other existing techniques.

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