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Automated Summarization of Text Documents using Deep Belief Networks

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ABSTRACT

In recent times, text summarization process becomes familiar as it generates a summary comprising a significant sentence from the original document. At the same time, automated extractive text summarization for lecture notes have gained popularity, which commonly collects important key points and sentences. The absence of a text summarization technique for lecture notes in the Tamil language motivated us to perform this study. In this work, a new automated text summarization model for Tamil Lecture Notes using Deep Belief Networks (DBN) has been presented. The proposed DBN model performs several processes namely preprocessing, sentence feature extraction, optimal feature selection, and summarization. The application of NLP for sentence feature extraction and DBN for selecting the optimal feature vector from the feature sentence matrix results in effective lecture note summarization. The performance of the DBN model has been validated using lecture notes of different subjects in Tamil language. The obtained experimental outcome showcased the superior performance of the DBN model over the compared methods.

Keywords: *Text summarization, Natural Language Processing, Deep belief network*

1. INTRODUCTION

Nowadays, the progressive development of the Internet and Big Data has intended to collect massive information regarding the required topic. Automated text summarization is highly applicable in summarizing significant sentences and encloses the meaningful details from actual content [1]. Henceforth, the essential details are received effectively from the actual document. The text consolidation was developed in the last decades, using a statistical model named as frequency diagrams. According to the documents received, single and multi-document consolidation is employed. Simultaneously, the final results are highly extractive and abstractive. The general process involved in text summarization is depicted in Fig. 1.

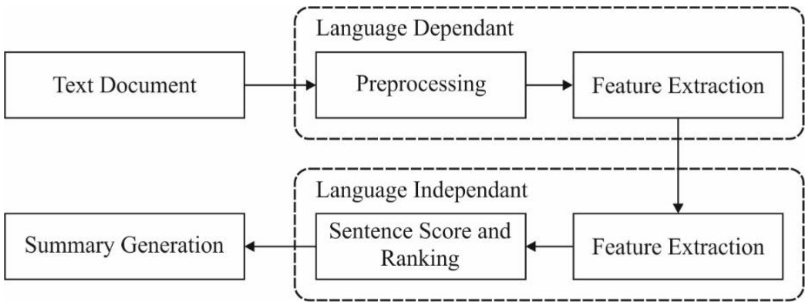

Fig. 1. Process in Text Summarization

Initially, a single document generates a summary that exists from a single source document and relevant documents are available. The different text summarization methods are classified in Fig. 2. In the meantime, multi-document consolidation is accomplished from diverse documents that describe a similar research topic. [2] Developed a text summarizing in a single document under the application of TF-IDF and automated text summarizing a single document with the help of Main Concepts. [3] consolidated various documents by applying the pattern-related summarization (Patsum) model on the DUC dataset which has exhibited better results when compared with term-based technology; however the ontology-related framework. [4] applied several documents under the application of Latent Semantic Analysis (LSA) as Non-Negative Matrix Factorization (NMF) and the simulation outcome has represented the high-tech with respect to precision as well as recall.

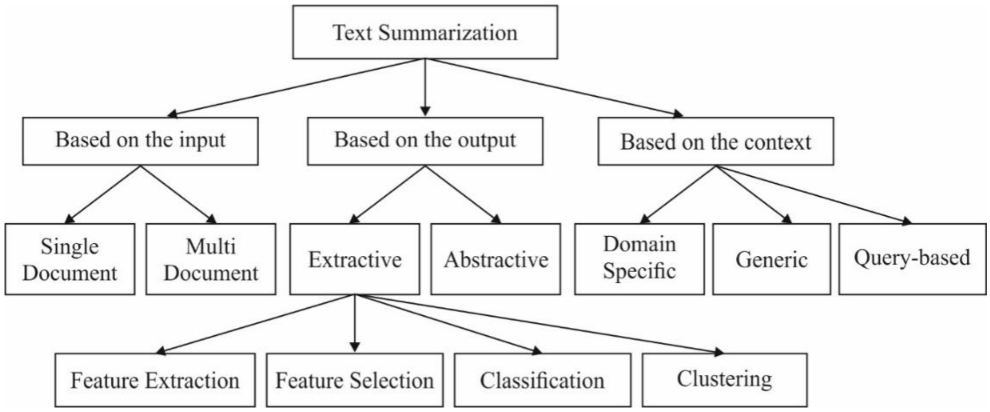

Fig. 2. Different text summarization methods

[5] Presented the summarization of Arabic single document that generates a creative summary integrating Machine Learning (ML) and score-relied methodologies which estimate the sentence dependent upon semantics and statistics. Finally, simulation outcomes are highly supreme by means of precision, storage, and F-scores, and the major limitation is that it feature weight is not optimized. [6] employed a model for suppressing the redundancy in multi-document consolidation by Shark Smell Optimization (SSO) technology and the outcomes outperformed the traditional mechanism. Extractive summarization is defined as a summary which collects the complete details where results of summary sentences are attained from the actual content. Usually, the threats involved from extractive summarization where the position is determined and words are arranged in sequence. Followed by, the extraction of the problem is named as Information Extraction (IE) for generating a summary with certain outcomes for accomplishing better accuracy. The instances of the automated summarizing method are deployed by using IE methods named as RIPTIDES, which summarizes the news relied on relevant scenarios.

In the case of the educational sector, automated extractive text summarization of lectures is an effective tool, extrapolating the key points with no human contribution. For MOOC, transcripts from video lectures are accessible; however, meaningful data from a lecture is highly challenging. In recent times, various efforts are made for resolving these issues, however various solutions are executed are outsourced in natural language processing (NLP) methods, which requires prominent maintenance because of inferior generalization. Because of these limitations, numerous outputs from defined tools are random in nature. Followed by, various Deep Learning (DL) models were developed for the state of the art results on massive applications like automated extractive text summarization. Because of the recent development in lecture summarization, it offers a RESTful API and Command Line Interface (CLI) tool which is facilitated as lecture transcripts for implementing effective services. Next, the background and related work for lecture summarization, models applied for developing a service, and results, as well as example summarizations, exhibits the generally employed models like TextRank.

No previous works have focused on the text summarization technique for lecture notes in the Tamil language, which inspired us to carry out this work. This paper develops a novel automated text summarization model for Tamil Lecture Notes using NLP and Deep Belief Networks (DBN). The proposed DBN model performs several processes namely preprocessing, sentence feature extraction, optimal feature selection, and summarization. The application of NLP for sentence feature extraction and DBN for selecting the optimal feature vector from the feature sentence matrix results in effective lecture note summarization. The performance of the DBN model has been validated using different dimensions.

2. LITERATURE REVIEW

[7] applied the rule base generates optimal precision, f-measure, and recall measures for Rule-Based Summarizers; however, it is not applicable for the massive dataset. Moreover, extractive summarizing studies are deployed using Neural Networks (NN) that has gained maximum attention from the researchers when compared to conventional models. Many studies were performed by [8] using the DL method on the basis of Feed Forward Neural Network (FFNN) for consolidating the single document with the advantage of generating extractive summary with no development of features by Rouge score and finally generated a coherent summary. Unlike extractive summarization, sentences are produced by using abstractive summaries for generating summaries with the help of words not present in sentences. Abstractive summaries are highly insignificant and complicated when compared with extractive summaries as abstractive summaries need dense NLP. An approach in abstractive summary is classified as the Linguistic approach and Semantic approach.

The instances of models which apply linguistic approaches like data-centric technologies and tree-centric models. The samples of these approaches apply semantic approaches like template-based as well as ontology-based methodologies. In recent times, abstractive summarizing is evolved from encoder-decoder mechanism as developed in [9]. Followed by, this approach is effective, and encoder-decoder technology is sufficient in changing parameters independently. Approach methods were employed in practical summarization are fuzzy-based and ML. The instance of a model that applies fuzzyoriented framework is named Fuzzy Logic (FL) with former Zadeh's calculus of linguistically quantified propositions that report extraction and real-world issues which intend to develop supreme results in terms of evaluation, however, semantic problems are resolved using semantic objects in t-norms are unclear. Fuzzy Formal Concept Analysis (Fuzzy FCA) which reports semantic and real-world issues. The sampling approach which employs ML technology is Incremental Short Text Summarization (IncreSTS) by [10] that is better in outlier handling, maximum efficiency, and reliability on target problems.

Rank-biased precision-summarization (RBP-SUM) by [11] is highly beneficial to reduce the redundancy problems by using rouge, but it is applicable in generating extractive summaries. Text summarization is a challenging one in NLP as it needs accurate text analysis like semantic analysis and lexical analysis for generating an effective summary. Moreover, an optimal summary should have significant details which have to be précised and embedded with non-redundancy, relevance, coverage, coherence, and readability.

In [12], a new text summarization model is presented for English and Bengali text by measuring the similarity among the sentences. The presented model is validated using online new portal, blogs, and so on. Another text summarization model is presented in [13] using LSTM-CNN based Abstractive Text Summarization (ATS) framework (ATSDL). The presented model operates on two major phases: extraction of phases from sentences and generation of text summary using DL model. In [14], a pre-trained decoder-only network is employed where the identical transformer Language model (LM) both encodes the source and creates the summary. In [15], an effective generic extractive text summarization technique called SummCoder for single document has been presented using three sentence selection measures namely sentence content relevance, sentence novelty, and sentence position relevance.

An improvement in the quality of text summarization process takes place in [16] by the integration of deep neural network techniques with word embedding technique. An abstractive Arabic text summarization technique is presented in [17], depending upon the sequence-to sequence recurrent neural network encoder decoder architecture. In [18], diverse types of text summarization process is carried out under the category of extractive and abstractive text summarization. In [19], the sematic text has been captured and preserved as the primary feature for document summarization. An automated summarization technique is presented by the use of distributional semantic technique for capturing semantic to produce high quality summary. In [20], an efficient Hierarchical Human-like deep neural network for ATS (HH-ATS) based on the procedure of how humans understand an article and write the equivalent summary.

3. THE PROPOSED DBN MODEL

The overall working principle involved in the DBN model is demonstrated in Fig. 3. As shown, the input lecture notes are initially preprocessed in three levels namely sentence segmentation, tokenization, and stop word removal. Then, the sentence feature extraction process takes place on the preprocessed data to generate the sentence feature matrix. Next, the DBN model gets executed to derive the enhanced feature matrix with unique feature values for every sentence. At last, the summary is generated from the scoring values and feature matrix. These processes are elaborately discussed in the subsequent sections.

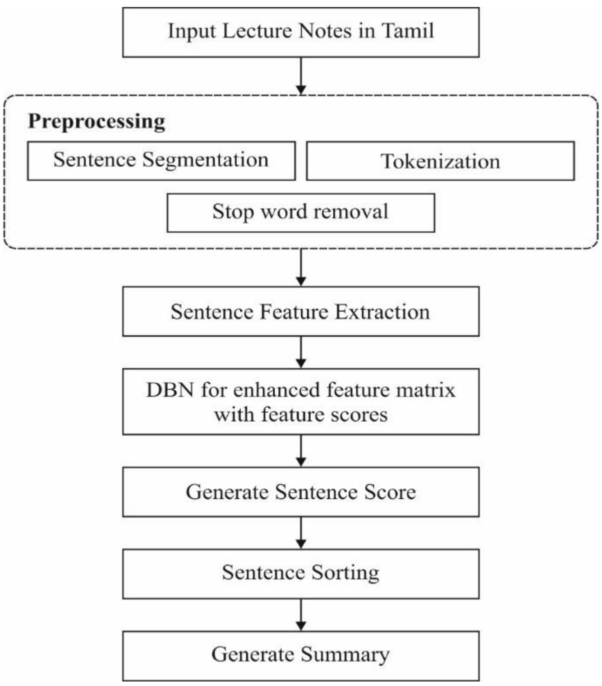

Fig. 3. Overall Process of Summarization using DBN

3.1. Preprocessing

The primary step of generating a summary is defined as input for text document with the format as .txt. Here, lecture notes applied in this principle should be in the Tamil language. Also, text files are incorporated under the application of tkinter python library. Hence, the input lecture notes undergo pre-processing with 3 stages such as sentence segmentation, tokenization, and stop word elimination. First, Sentence Segmentation, a complete text is divided into sentences and arranged in array format by means of sentence positions. Secondly, Tokenization, the sentences accomplished is again divided into words for feature estimations. It is operated with identifying sentences, count of paragraphs, and count of words in a passage. The main aim of sentence identification is to obtain all sentences. A sentence could be completed by using termination, full stop, etc. A specific effort has to be made for verifying the full stop after a capital letter.

The operation involved in token extraction also counts the number of paragraphs in the same passage. Paragraphs are counted using the given steps:

- Estimate the count of entering keys in a passage;
- When massive enter key occurs prominently, then it referred to as one;
- The overall count of enter keys represents the paragraph count.

Finally, word count is to identify overall words in the actual passage. By estimating the count of words in a passage the given steps have to be followed:

- Reading sentence by sentence;
- With the help of StringTokenizer.countTokens () in java provides several words;
- Consolidating the Count values shows a word count.

For accomplishing a productive summary, only specific words have to be assumed as stop words, and no weights are allocated. Then, a database is developed for listing all stop words. The key objective of this portion is to gather the remaining words.

3.2. Sentence Feature Extraction

Once the Pre-processing is completed, sentence features have been determined for identifying a sentence value. There are some sentence features in selecting a sentence value:

Sentence Position: Based on the sentence location, the relevance is learned. In [21], the developer recommends that an initial and final sentence of a lecture note is highly vital with essential details. The position feature is determined under the application of (1).

$$Sent.Pos. = \begin{cases} 1, if firstorlastsentence \\ \dfrac{N-P}{N}, if others \end{cases} \tag{1}$$

where N implies an overall sentence, P denotes the sentence's position.

Sentence Length: In short sentences do not have important details. The essential information can be found using sentence length and feature score is evaluated using (2).

$$Sent.Len_i = \frac{wordsinsentence_i}{wordsinlargestsentence} \tag{2}$$

Numerical Token: it is defined as an overall numerical score in a sentence which is measured using (3).

$$NumericaltokenScore_i = \frac{num\_numeric_i}{len} \tag{3}$$

where, num $numeric_i$ refers to numerical tokens in i^{th} sentence and len signify entire words in i^{th} sentence.

TF-ISF: The TF-IDF is very significant for systems in data retrieved. Here, text summarization is performed in a single lecture note. Thus, TF-ISF is determined by using (4).

$$TFISFscore = \frac{(\log(isf) * (tf))}{len} \tag{4}$$

Where, isf means an entire occurrence of i^{th} sentence, tf represents a term frequency of a i^{th} sentence and len refer entire words in i^{th} sentence.

Cosine similarity between Sentence and Centroid: Centroid is a sentence with massive TF-ISF. Cosine similarity with a centroid is estimated to all sentences as provided in (5).

$$Cos_{sim}i = \cos(sentence_i, centroid) = \frac{sentence_i.centroid}{\|sentence_i\|\|centroid\|} \quad (5)$$

Bi-Gram: It is the pair of 2 adjacent words developed for all sentences in a lecture note. NLTK library has been applied for identifying the total values of bi-grams in a sentence. The feature score undergoes normalization for limiting the feature values from 0 and 1.

Tri-Gram: It is a triple of 3 adjacent words developed from a sentence in a lecture note. NLTK library has been applied for identifying the count of tri-grams in a sentence. The feature score undergoes normalization for limiting the values among 0 and 1.

Proper Noun: it is a noun that refers to an exclusive identity such as name, place, and so on. Here, the total no. of proper nouns is determined utilizing (6). Useful proper nouns can be measured using the sentences are POS tagged using NLTK.

$$Propernounscore_i = \frac{No.ofpropernouns_i}{Sentencelength_i} \quad (6)$$

where No. of proper $nouns_i$ signifies the no. of proper nouns in i^{th} sentence and sentence $length_i$ defines the no. of entire words in i^{th} sentence.

Thematic Words: It is keywords in all sentences that are domain-specific. The no. of thematic words is measured utilizing (7).

$$Thematicword_i = \frac{No.ofthematicwords_i}{Totalno.ofthematicwords} \quad (7)$$

where, No. of thematic $words_i$ shows the no. of thematic words in i^{th} sentence.

3.3. DBN based Enhanced Feature Matrix Determination

Once the sentence features are estimated, a sentence feature matrix has been developed. Here, a sentence is comprised of 9 feature values. The feature values are not fixed and are based on the relied number of features. Then, the DBN model is applied to determine the enhanced feature matrix [22]. The DBN are mainly comprised the background of Restricted Boltzmann Machines (RBMs) that are the beginning of DBN understanding. Basically, the RBM is an energy-based stochastic NN created by 2 layers of neurons that are visible as well as hidden nodes, where the learning steps are performed in an unsupervised fashion. The structural design of RBM has a visible layer v with m nodes and a hidden layer h with n nodes.

In a $m \times n$ matrix, W models the weights among visible as well as hidden layers, where w_{ij} refers to the weight among visible node v_i and hidden node h_j. Assume that v and h are the binary and hidden units, correspondingly, $y \in \{0,1\}^m$ and $h \in \{0,1\}^n$. An energy function of RBM is provided by:

$$E(v,h) = -\sum_{i=1}^{m} a_i v_i - \sum_{j=1}^{n} b_j h_j - \sum_{i=1}^{m}\sum_{j=1}^{n} v_i h_j w_{ij} \quad (8)$$

where the vector a and b are the basis vectors of visible and hidden layers, more, the possibility of the provided configuration (v,h) is calculated as follows:

$$P(v,h) = \frac{e^{-E(v,h)}}{\Sigma_{v,h} e - E(v,h)} \quad (9)$$

The denominator refers to every feasible configuration (v,h), that is herein a normalization factor. The parameters a, b and W of RBM is optimized by utilizing stochastic gradient scent on the log -possibility of training data models. The probability of a provided sample is calculated over every feasible hidden vector by (3).

$$P(v) = \frac{\Sigma_v e^{-E(v,h)}}{\Sigma_{v,h} e - E(v,h)} \quad (10)$$

Fig. 4 depicts the structure of the DBN model. The stochastic gradient ascent technique calculates the derivatives of the logarithm of $P(v)$ through appreciated to $a, b,$ and W, and then leading to equations as follows:

$$W^{t+1} = W^t + \eta(P((h|v)v^T - P(\tilde{h}|\tilde{v})\tilde{v}^T) - \lambda W^t + \alpha \Delta W^{t-1} \quad (11)$$

$$a^{t+1} = a^t + \eta(v - \tilde{v}) + \alpha \Delta a^{t-1} \quad (12)$$

$$b^{t+1} = b^t + \eta(P\left((h|v) - P(\tilde{h}|\tilde{v})\right) + \alpha \Delta b^{t-1} \tag{13}$$

where

$$P(h_j = 1|v) = sigm\left(\sum_{i=1}^{m} w_{ij} v_i + b_j\right) \tag{14}$$

and

$$P(v_j = 1|h) = sigm\left(\sum_{i=1}^{n} w_{ij} h_i + a_j\right) \tag{15}$$

where η, n, λ, α are the parameters of learning rate, hidden node count, weight decompose, and momentum weight. The $sigm(\cdot)$ refers to the logistic sigmoid function. A set of three learning techniques namely Contrastive Divergence (CD) and Persistent Contrastive Divergence (PCD) are executed to learn the weight matrix and the equivalent bias vectors of the visible as well as hidden nodes.

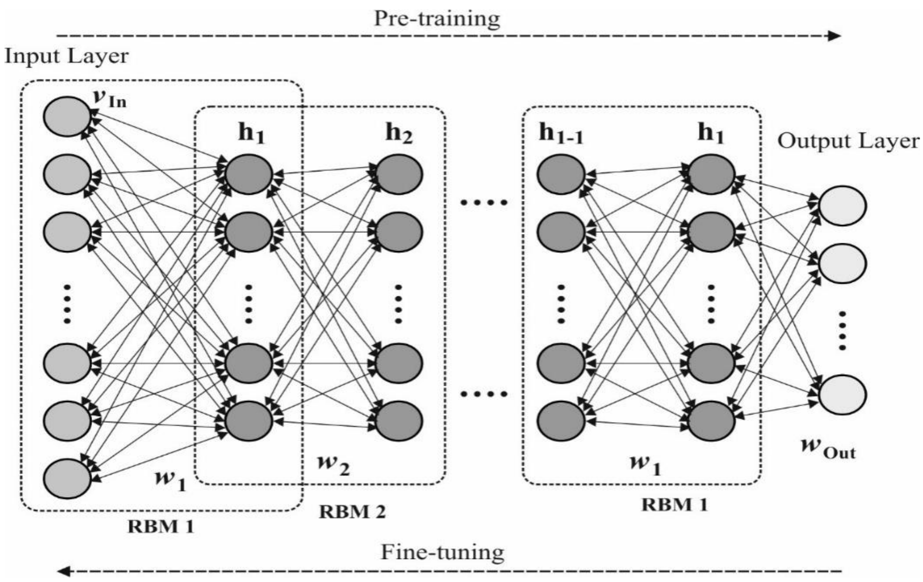

Fig. 4. Structure of DBN

Consider a DBN with L layers and the W^i the weight matrix of RBM at layer i. Furthermore, it determines the hidden units at layer I are the input units to layer $i + 1$. In fine-tuning steps to train all RBMs. The presented model is implemented by means of a back-propagation technique and Gradient descent technique for altering the matrices $i = 1,2, \dots .L$. The optimization for finding the minimization of error measure regarding the outcome of a further layer placed on the top of the DBN following its former greedy training namely softmax or logistic units.

3.4. Summary Generation

At the summarization stage, the accumulation of every enhanced feature value for every individual sentence in the lecture not is determined and saved in a list form. Therefore, a value is created for every lecture note, indicating its score. Based on the score, the sentence is sorted in descending order. The summary usually contains the initial sentence and the rest of the sentences are summarized based on the score.

4. EXPERIMENTAL VALIDATION

In this section, a detailed results analysis of the proposed DBN model takes place in terms of different performance measures under a varying number of documents. For training process, a total of 30 documents were used whereas 6 documents are employed for testing process. Table 1 investigate the lecture notes summarization results of the DBN model. On the applied document 1, the presented DBN model has resulted in better performance with the higher precision of 0.87, recall of 0.84, and F-score of 0.85.

Table 1: Result Analysis of Proposed DBN Method in terms of Different Measures

Number of Documents	Precision	Recall	F-score
Document 1	0.87	0.84	0.85
Document 2	0.89	0.85	0.86
Document 3	0.92	0.88	0.89
Document 4	0.86	0.84	0.84
Document 5	0.91	0.86	0.87
Document 6	0.94	0.81	0.92
Average	**0.90**	**0.85**	**0.87**

At the same time, on the applied document 2, the DBN model has depicted slightly higher results with the precision of 0.89, recall of 0.85, and F-score of 0.86. Simultaneously, on the applied document 3, the DBN model has showcased effective performance with the precision of 0.92, recall of 0.88, and F-score of 0.89. Furthermore, on the applied document 4, the DBN model has displayed satisfactory results with the precision of 0.86, recall of 0.84, and F-score of 0.84. Along with that, on the applied document 3, the DBN model has demonstrated better results with the precision of 0.91, recall of 0.86, and F-score of 0.87. Concurrently, on the applied document 5, the DBN model has shown proficient performance with the precision of 0.94, recall of 0.81, and F-score of 0.92. Finally, the proposed DBN model has exhibited acceptable results with the precision of 0.90, recall of 0.85, and F-score of 0.87.

Table 2: Result Analysis of Proposed DBN with different text summarization models

Methods	Precision	Recall	F-score
Proposed DBN	0.90	0.85	0.87
SGM	0.42	0.31	0.35
GA Model	0.87	0.72	-
RS Model	0.47	0.24	-
CA Model	0.75	0.53	-
RBM	0.82	0.77	0.79
RBM-FL	0.88	0.80	0.84

Table 2 portrays the comparative results analysis of the DBN model with a set of existing methods namely Semantic Graph Method (SGM) [23], Random Selection (RS) [24], Centroid Approach (CA) [25], and RBM with FL (RBM-FL) [26] in terms of different measures. On determining the summarization results in terms of precision, the ineffective results are provided by the SGM and RS models with the least precision value of 0.42 and 0.47 respectively. In line with, the CA model has showcased slightly better performance with the precision value of 0.75. Along with that, the RBM model has resulted in moderate summarization results with the precision of 0.82. On continuing with, the GA model has tried to surpass all the compared methods except RBM-FL and NLP-DBM models with the precision of 0.87. Though the RBM-FL model has portrayed competitive performance with the precision of 0.88, the DBN model has attained superior results with a maximum precision of 0.9. Similarly, on investigating the summarization outcome of the DBN model in terms of recall, the RS model has exhibited worse results with the minimum recall value of 0.24 whereas the SGM model has resulted in a slightly higher recall of 0.31. At the same time, the CA model has depicted a manageable summarization outcome with the recall of 0.53.

Concurrently, the GA model has shown manageable performance with the recall of 0.72.

Next to that, the RBM model has achieved a reasonable performance with the recall of 0.77 whereas an even higher recall of 0.8 has been attained by the RBM-FL model. However, the proposed DBN model has achieved a better summarization outcome with a higher recall of 0.85. Finally, on investigating the Tamil lecture notes summarization results of the DBN model, the SGM model has failed to show acceptable results by attaining a lower F-score of 0.35. In addition, the RBM and RBM-FL models have resulted to a manageable outcome with moderate F-score values of 0.79 and 0.84. But the proposed DBN model has exhibited outperforming results over the previous models with the higher F-score of 0.87.

5. CONCLUSION

This paper has introduced an effective automated text summarization model for Tamil Lecture Notes using the DBN model. The proposed DBN model performs several processes namely preprocessing, sentence feature extraction, optimal feature selection, and summarization. The input lecture notes are initially preprocessed in three levels namely sentence segmentation, tokenization, and stop word removal. Then, the sentence feature extraction process takes place on the preprocessed data to generate the sentence feature matrix. Next, the DBN model gets executed to derive the enhanced feature matrix with unique feature values for every sentence. At last, the summary is generated from the scoring values and feature matrix. The application of NLP for sentence feature extraction and DBN for selecting the optimal feature vector from the feature sentence matrix results in effective lecture note summarization. The experimental results of the DBN model are validated and the results are examined under distinct aspects. The simulation outcome verified the effective summarization performance of the Tamil lecture notes over the existing methods. In future, the proposed DBN model can be utilized in real-time educational institutions to summarize the lecture notes for easier understanding to the students.

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