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Original Article

A Content Recommendation System for Effective E-Learning using Semantic Fuzzy Humming birds Optimization and RoBERTa

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Abstract – *E-learning plays a major role in this pandemic for learning the subjects in depth through self-learning. In this e-learning process, the study materials are useful for the learners to learn their interested subjects deeply with good understanding. Identifying suitable and most useful materials is very difficult today due to the availability of huge relevant materials online. For identifying suitable study materials, the various content recommendation systems are available for providing suitable study materials to the learners. Even though the available content recommendation systems are not fulfilling the current requirements, for this purpose, we propose a new content recommendation system that applies a newly proposed semantic fuzzy optimality aware hummingbirds optimization technique and the enhanced version of the Bidirectional Encoder Representations from Transformers (BERT) called Robustly optimized BERT Pretrained Approach (RoBERTa)for identifying the more relevant content to the e-learners according to their interests and learning capability. In this work, the semantic similarity score is calculated for each study material and considered the fuzzy optimality result as input for the hummingbirds' optimization technique for identifying the more relevant terms that are meaningful and used to find suitable study materials. Finally, the RoBERTa is applied for categorizing the relevant, irrelevant, and most useful documents from the available online, local repository, and dataset. The experiments have been conducted to evaluate the proposed system and proved that as better than the existing systems in terms of precision, recall, f1-measure, and prediction accuracy.*

Keywords – *E-learning, LSTM, Content recommendation system, Fuzzy optimality, and Optimization.*

1. Introduction

Recently, people are utilizing the high-speed internet facility for completing their day-to-day life sophistically. Most companies and organizations are trying to enhance their service quality by fulfilling customer requirements with the help of technology. Generally, the technology is widely used in the education environment to enhance the quality and facilitate the knowledge shared among the learners in the world [1-3]. High-skilled people share the study materials and useful content with learners worldwide [4-5]. The application of web-based software permits to learn of the subjects reliably through distance mode [6]. E-learning is an important platform for sharing content through the internet that permits people to share their knowledge worldwide, which is useful for enhancing the e-learner's capability. The e-learning system improves the learners' learning capability than those studying physics in an educational institute [7-9]. Finally, the e-learning system is helpful for people who cannot spend the amount to learn the latest technology. The researchers and the advanced learners use the recommendation systems to filter the irrelevant contents and retrieve personalized data. The learners have various requirements for their interests, needs, and learning capabilities. In this scenario, the content recommendation systems are getting more attention from the e-learners for extracting more suitable and relevant documents to learn any subject or technology easily (Dwivedi & Bharadwaj 2015).

Semantic analysis plays a vital role in text classification and content recommendation due to the availability of vast irrelevant data on the internet and other repositories. This analysis helps identify the relevant contents from the available text/document by analyzing the meaning of the contents. The similarity score is calculated according to the relevancy in terms of semantic score. The semantic similarity score is calculated by considering the semantically matched contents. Fuzzy logic is widely applied in various fields, including medicine, to make accurate patient record decisions. The medical reports are analyzed to determine whether they report it is semantically meaningful and relevant.

Moreover, how much the term is relevant to the target term is also calculated by applying the fuzzy membership functions and fuzzy rules that are constructed according to the specific fuzzy membership function intervals. A feature optimization process helps enhance the content recommendation and prediction accuracy performance. Identifying a more relevant term or feature is important to reduce the dataset/content/document size. Generally, the feature optimization is done by applying standard optimization algorithms such as Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing, Harris Hawkins, Grey-Wolf Optimization Algorithm, Spotted Hyena Optimization algorithm, etc. These are all the optimization techniques used for optimizing the features effectively.

The deep learning technique is widely used for analyzing the data/content/document in depth by conducting the training process deeply to identify the suitable pattern for performing the data classification. The various deep learning algorithms, namely Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long-Short Term Memory (LSTM), Deep Belief Network (DBN), Deep Neural Network (DNN), and Multilayer Neural Network (MNN) are available in the literature for performing deep learning and classification. These kinds of algorithms are more useful for improving the classification performance than the Machine Learning algorithms such as C4.5, Decision Tree (DT), Multilayer Perceptron (MLP), Artificial Neural Network (ANN), Support Vector Machine (SVM), Multiclass Support Vector Machine (MSVM), etc. Many deep learning algorithms are available in the literature for enhancing classification accuracy. According to the input data, the deep learning algorithm usage and performance vary. CNN is the best choice for image classification, and the RNN and LSTM are the dominant deep learning algorithms for categorizing the text/content/document. So, this work applies LSTM for categorizing the text as relevant and irrelevant according to the user's interests and learning capability.

Natural Language Processing (NLP) Transformers is an advanced version of the deep learning technique in text analysis. The Bidirectional Encoder Representations from Transformers (BERT) algorithm is used for analyzing the text and provides a better result analysis. The advanced version of the BERT algorithm is called the Robustly optimized BERT Pretrained Approach (RoBERTa) for performing the text analysis. These algorithms perform the masking in BERT training, sentence prediction, text encoding, and training batch size. This work applies RoBERTafor performing the effective text/document categorization.

The major contributions are listed below:

1. To propose a new content recommendation system for recommending suitable content to the e-learners for ease of understanding the subjects.
2. To develop a new semantic similarity and fuzzy optimality aware hummingbirds feature optimization technique to select the most suitable key terms that are useful for identifying the most relevant content.
3. To apply the standard RoBERTa for categorizing the content as relevant and irrelevant.
4. To be proved that the proposed system is better than the existing e-learning system in terms of precision, recall, f-measure, and prediction accuracy.

The rest of this paper is organized as below: The related works in the direction of the proposed system are discussed by highlighting the merits and demerits in section 2. The overall architecture of the proposed system is explained in section 3. Section 4 describes the background information about the proposed optimization technique and the RoBERTa. Section 5 provides the experimental results of the proposed system and the comparative results. Section 6 concludes the proposed work with future works.

2. Literature Survey

Various researchers have developed many content recommendation systems in the past for ease of understanding the subjects and concepts in e-learning, incorporating fuzzy logic and temporal constraints, semantic analysis, sentiment analysis, and deep learning. Among them, Anido et al. (2001) described the functionalities of the SimulNet and authoring software used to share the features that help learn the subject easily. Colace and De (2010) discussed in detail the role of ontologies on e-learning systems with the incorporation of a new method built by using a Bayesian network. In the end, they proved their method by conducting various experiments. Shishehchi et al. (2010) developed a new semantic aware recommendation system to recommend suitable learning material for learners. They have used the ontology and web ontology language rules for filtering the materials that are helpful to understanding the subject. Finally, their system proved better than the existing systems regarding recommendation accuracy. Brut et al. (2011) presented a solution for extending the ontology and semantic annotation aware learning object modelling for retrieving the relevant documents. Their technique is the structure-based index method, latent semantic indexing, and linguistic method for text processing. Finally, they have achieved better recommendation accuracy quickly. De et al. (2012) developed a new method for improving the experience of personalized e-learning that is used to learn the learners' expectations and activities by categorizing the materials according to the users' interests and learning capability. Garrido and Morales (2014) presented an effective method for extracting the metadata information from the e-learning materials to learn the subject easily by analyzing the learning objects and styles of the users.

Wu et al. (2015) proposed a personalized recommendation system incorporating fuzzy tree-structured learning and learner profile methods. These methods help identify the semantic relationship between the learning activities and needs. They have proved that their system is better than other systems regarding recommendation accuracy. Khodke et al. (2016) focused on neuro-fuzzy-aware methods to learn the subjects easily through e-learning, incorporating fuzzy logic, fuzzy tree matching, fuzzy clustering, and ontology. They have concluded their work by identifying the importance and role of fuzzy logic in e-learning along with neural classifiers. Fei et al. (2016) proposed a new method that considers the ranking techniques to rank study materials according to the users' interests. Shimaa et al. (2017) conducted a detailed analysis to address the usage of ontology and also proposed a new ontology-based eco-system to enhance the personalized learning process. Perumal et al. (2017) proposed a new fuzzy content recommendation system for ease of learning online by recommending suitable content to the learners. They have developed a new fuzzy family tree to identify the relevant content and rank them. Finally, they have achieved better recommendation accuracy than other systems.

Abdelaziz et al. (2019) created a new learning environment for carrying out semantic reasoning and user relationships. They have combined the web semantics and the social networks by integrating the semantic knowledge and designing an ontology. In their work, they first understand the user's expectations and the relevant resources and categorize the various resources. Finally, they have presented a method to detect the student communities for sharing their interesting resources. Anatoly et al. (2019) developed a new semantic-aware multi-agent method that allows students to retrieve the required data dynamically using e-learning applications. Nafea et al. (2019) developed a new recommender method that considers student ratings, learning objectives and styles. They have applied the Felder-Silverman learning style to represent the learning object and style. They conducted experiments using 80 students to learn the course styles and methods. Finally, they have proved that their method is better than others regarding recommendation accuracy. Aminu et al. (2020) developed a new deep learning technique that incorporated a recommendation system that applies the aspect of aware opinion mining to enhance the recommendation accuracy. They have used a multichannel deep CNN in their system to retrieve the data and generate the ratings according to the different aspects. Moreover, they also integrated the aspect rating with tensor factorization to predict the rating. Finally, they have achieved better performance than other systems.

Soulef et al. (2021) developed a new learning environment that provides personalized content to e-learners. They have designed an association rule incorporated recommendation system for recommending suitable learning material to the users according to their learning capacity. Carbone et al. (2021)

Feng et al. (2021) developed a two-stage recommendation system for recommending suitable learning materials with the help of a collaborative filter and decomposition-aware multi-objective optimizer. Sunny et al. (2021) developed a new semantic aware personalized recommendation system that dealt with the semantic gap between high- and low-level semantic contents. They have recommended suitable videos to the users for exploiting the domain ontology and the relevant contents in their work. Finally, they evaluated their system and determined the prediction process and ratings according to its accuracy. Ravita and Sheetal (2021) developed a new deep semantic structure model that applied sparse semantic data and represented the skills. They have used two datasets as CareerBuilder. Com and Naukari.com evaluated their model, provided promising results, and proved better than other models. Jeevamol et al. (2021) presented a detailed analysis of the content recommendations available in the direction of e-learning. They have collected the relevant works published between 2015 and 2020 and categorized and analyzed the various techniques, inputs, procedures, and evaluation parameters. Finally, they have highlighted the merits and demerits of the works.

Aminu et al. (2021) developed a new recommendation system for exploiting the neural network and methods for learning the user representation and also fine-grained the user interested items and interaction to improve the recommendation accuracy. In their work, they have designed the pooling layer of CNN for learning the latest features and capturing important data. Finally, they applied a prediction layer to predict the user item and interests and proved them better than others through various experiments conducted using the Amazon dataset. Xiaofei et al. (2021) developed a new neural network-based microblog sentiment classifier that learns the various learning representations by exploiting the user's historical and contextual data. Their classifier considers the various encoders such as micro-post, historical users sentiment, and semantic user encoders. Karthik and Ganapathy (2021) developed a new fuzzy recommendation system for predicting the relevant products to the customers in online purchases. They have developed new algorithms for calculating the sentiment score for the available products. Finally, they have generated new fuzzy rules that help predict the suitable products for the customers through the ontology-aware recommendation system.

Hadi et al. (2022) designed a new framework incorporating the enhanced hybrid recommendation system for e-learning. They have used two different semantic aware ontologies such as WordNet and DBpedia. In addition, the different sentiment analysis techniques are also developed and used for predicting the e-learning materials that help enhance the understanding and learning capability. Finally, they have achieved better performance than the existing systems regarding prediction accuracy. Nut et al. (2022) discussed the various ontological technologies for content recommendation. They have identified around 30 articles in the direction of ontology-based content recommendation systems that combines the artificial intelligence concept, education method, and social scenario. In their model, the ontology-based recommendation system was seldom applied and also evaluated the students' real situations, performance, assessments, and other qualitative observations. Finally, they have concluded that the recommendation systems are useful for improving the courses in online learning. Miao et al. (2022) developed a deep basket and sensitive, aware factorization mechanism for addressing the task. They combined the low and high-order feature patterns to capture the structures from the input data or contents. In the end, they applied a linear method for integrating the various results and proved their work better than other models by using three different live datasets.

Mansoureh et al. (2022) recommended a new method for creating a learning automata-aware user profiling. They used a clustering algorithm to gather the items according to the feature relevancy. Moreover, they have incorporated an automation system for finetuning users' interests according to their feedback. Finally, their method outperforms other methods regarding precision, recall, and RMSE. Idris et al. (2022) developed a new model that considered the sentiment score and LSTM as an adaptive LSTM for high recommendation and prediction accuracy. They have considered the three different live streaming datasets from Amazon review history for conducting experiments and proved the efficiency of their model. Xin et al. (2022) developed a new recommendation system that considers the temporal constraints according to the dynamic user's preferences. First, they have developed a new topic model incorporating the time constraints and the Markov model for predicting the user's interests and integrating the products' attributes and preferences to rank them. Finally, their system recommends suitable products to the users.

Seungyeon and Dohyun (2022) developed a new recommendation system that applies CNN for identifying the suitable items for the respective users by applying the outer product matrix. Their system handles the various features and also captures meaningful data. In addition, they alleviated the overfitting issues, and their method incorporates the max pooling on behalf of the fully connected layers. Finally, their system achieved better performance in terms of recommendation accuracy. Xin et al. (2022) developed a new recommendation system according to the users' choices from their posted queries. In their system, they have considered the time constraints, users interests, and search history detail for predicting the product according to the product ranks. In the end, they have recommended the relevant products to the customers. All the available works are not achieved much recommendation accuracy and short period. It is not fulfilling the current learners' requirements due to the availability of the volume of content related to all the subjects and topics. For handling the vast content, a new content recommendation system is proposed in this work to recommend the most suitable study material to the e-learners quickly and fulfill the learners' requirements by applying the newly proposed semantic aware feature optimization algorithm and LSTM.

3. System Architecture

The proposed system architecture is demonstrated in figure 1, which consists of eight components: dataset, user interaction module, decision manager, feature optimizer, content recommender, knowledge base, rule base, rule manager, and fuzzifier.

The user interaction module collects the necessary data according to the users' queries with the help of the decision manager. Initially, it retrieves the relevant document from an online repository and forwards it to the decision manager for further process. The decision manager conducts the semantic analysis and calculates the semantic similarity score, performs the fuzzy optimality process by applying the fuzzy optimality method, and applies the existing hummingbird's optimization algorithm to consider the selected input key terms

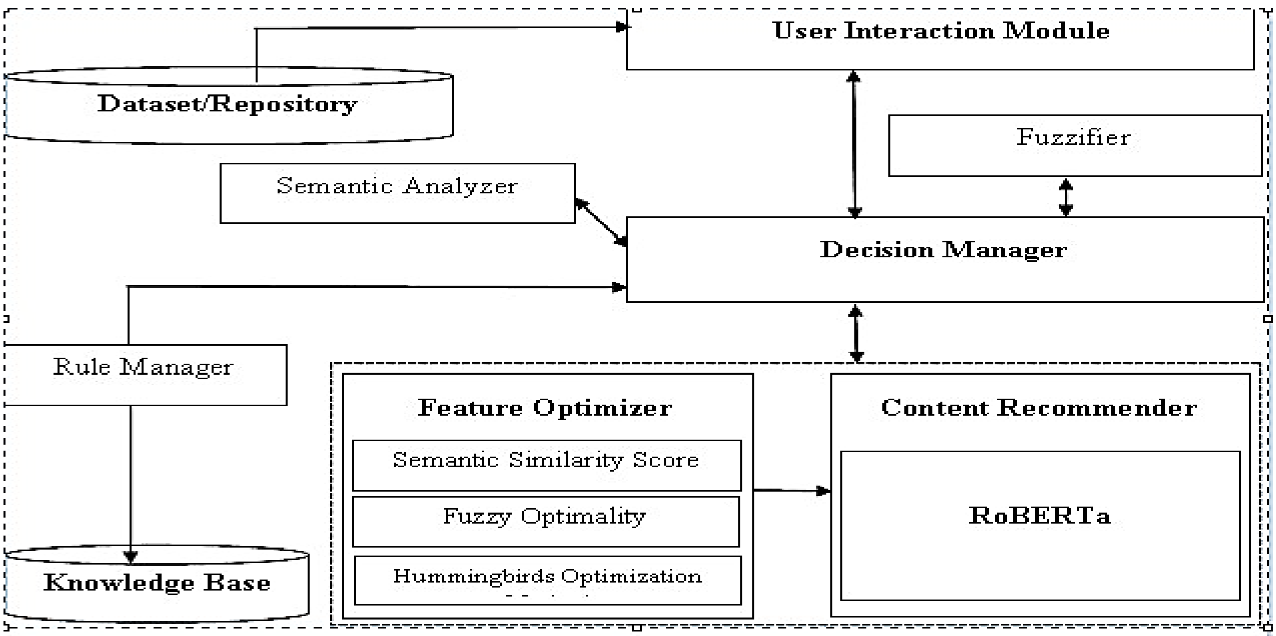

Fig. 1 Overall System Architecture

Finally, the decision manager selects the most suitable key terms at the end of the fuzzy optimizer phase and is forwarded to the content recommender for recommending the suitable content by applying the RoBERTa algorithm. Moreover, the decision manager uses the fuzzifier and semantic analyzer to perform the feature optimization process. In addition, it applies the rules available in the knowledge base through the rule manager. The user interaction module will send the recommended document to the requested users.

4. Proposed Work

The proposed content recommendation system is explained in detail with necessary background information and the proposed model. The proposed model is used to recommend the more relevant and suitable document or the study material to the learners for ease of understanding the concepts of their interesting subjects. The proposed model consists of two important phases: feature optimizer and content recommender. In the feature optimizer phase, it applies a newly proposed algorithm called semantic and fuzzy optimality aware hummingbirds optimization algorithm to optimize the features effectively. The semantic similarity score is calculated for the input data or content to identify the more relevant key terms. Then, the fuzzy optimality technique is incorporated to choose the effective and more relevant content and the semantically more relevant contents and give as input to the hummingbird's optimization algorithm and finalize the most relevant key terms that are useful for enhancing the classification accuracy. The text classification is done in this work using RoBERTa per the users/learners' requirements and expectations. First, this section explains the semantic similarity method.

4.1. Semantic Similarity

This section explains the semantic similarity between two different subsections, such as an inferred semantic network. Generally, the semantic network highlights the virtual or live links from one concept to another in the various resources and materials(Allen & Frisch, 1982). In this work, the concepts can be connected by considering semantic relevancy. In addition, the Dijksra algorithm (Dijkstra 1959) is applied to find the shortest path between the classes. Some rules and regulations are used to handle the sources and study materials classes here. The major modification operation is done by changing the method used for calculating the path between different classes and the term "Thing" for computing the path between any combinations of the concepts in this work. The weights are assigned according to work (Ge &Qiu, 2008) for the key terms identified in this work. In addition, these changes are accepted for computing the distance from one node to another node in the semantic network. This step is used to finalize the number of edge weightages from any class to the "Thing" that is a root by applying the formula given in equation (1).

$$W(x, y) = 1/2level(y) \quad (1)$$

x and y are pairs of classes in the semantic network. The semantic distance between the nodes is calculated using equation (2).

$$Semantic\_Distance(x, y) = \sum z \in shortestPath(x, y)\ Wz\ (x, y) \quad (2)$$

z is the path from x to y. Then, the semantic distance between the two classes is computed using the formula in equation (3).

$$Distance\ (x,\ y) = Semantic\_Distance\ (x,\ Thing) + Semantic\_Distance\ (y, Thing) \quad (3)$$

Where the variable thing indicates the newly added root to all the different concepts that are available in the semantic network. The variable SD represents the shortest path between similar kinds of concepts in the network. Finally, the semantic similarity between the two classes is calculated using the equation (4).

$$Semanticsimilarity\ (x, y) = 1\ Distance\ (x, y) + 1 \quad (4)$$

The semantic similarity value is calculated by using the following steps:

1. Find the cosine similarity from one concept to another one concept by applying the formula given in equation (5)

   $$CosineSim\ (d1\ ,2\ ) = \sum ni=1\ d1 * d2\ \sqrt{\sum ni=1}\ d1\ i2 * \sqrt{\sum ni=1}\ d2\ i2 \quad (5)$$

   $d1$ indicates the vector value that represents the initial level idea, and d2 represents the vector value that indicates the second definition.
2. Compute the mean value of the common SubClassOf and SuperClassOf from one pair of concepts to another pair of concepts.
3. Perform the reasoning process through the comparative analysis between the pair of concepts and connect the parents and children as subClassOff or superClassOf.
4. Find the average findings of the children and parents that are interpreted by using the formula given the equation (6).

   $$S(x, y) = (Avg(SCO) + Avg(SPRCO) + CS) \quad (6)$$

   Where SCO indicates the shared sub-class between x and y, SPRCO indicates the shared superclass between x and y and the conceptual similarity between x and y.

The steps above are followed to calculate the semantic similarity score between the classes and are considered separate results. It forwards to the next phase, which is fuzzy optimality. The fuzzy optimality is explained in the next subsection.

4.2. Fuzzy Optimality

The basic concepts of fuzzy optimality are explained in detail with necessary formulae in this subsection. The fuzzy optimality is performing the next level of feature optimization in this work. The fuzzy optimality is explained in this work for ease of understanding. The major objective of the candidate solutions is expressed in the form of a matrix given in equation (7).

$$F(CVS) = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1k} \\ f_{21} & f_{22} & \cdots & f_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ f_{S1} & f_{S2} & \cdots & f_{Sk} \end{bmatrix} \quad (7)$$

Where k indicates the number of objective functions, S represents the number of independent variables, and the variables f_{ij} and w_i are hold the crisp numbers where $i \epsilon (1, 2, \ldots, S), j \epsilon (1, 2, \ldots, k)$.

In various situations, the crisp numbers are insufficient to simulate current situations, the human predictions and recommendations are uncertain and vague, and they cannot estimate the quantitative keywords. Zadeh developed the fuzzy set theory to resolve the issues such as ambiguity and vagueness of human decisions that can process the input data using fuzzy intervals [22]. According to the basic idea, every value of the objective method f_{ij} is converted into a triangular fuzzy member function $f_{ij} = (f_{ij}, f_{ij}, f_{ij})$, and the candidate solutions values are described in the equation (8).

$$\bar{F}(CVS) = \begin{bmatrix} \bar{f}_{11} & \bar{f}_{12} & \cdots & \bar{f}_{1k} \\ \bar{f}_{21} & \bar{f}_{22} & \cdots & \bar{f}_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ \bar{f}_{S1} & \bar{f}_{S2} & \cdots & \bar{f}_{Sk} \end{bmatrix} \quad (8)$$

Human beings cannot calculate the values exactly on the dataset in a vague and uncertain situation. Generally, the preferences can be expressed as "More Relevant," "Relevant," "Partially Relevant," and "Irrelevant." The fuzzy optimality preferred the data linked with fuzzy triangular intervals and then processed based on the above-mentioned fuzzy operators. For example, the three preferences are positive such as {"More Relevant", "Relevant", "Partially Relevant", "Irrelevant"} that are mapped with the numbers {(0.8, 0.8, 0.9), (0.6, 0.6, 0.7), (0.4, 0.4, 0.5), (0, 0.1, 0.1)}. Here, the options are provided in the format of the fuzzy membership directly, and the vector is mentioned as $\widetilde{w} = [\widetilde{w}_1, \widetilde{w}_2, \ldots \widetilde{w}_k]$.

The computational flow of the fuzzy optimality is explained below with the necessary steps are as below:

Step 1: The linguistic variables are mapped as different data preferences in the form of the vector is $\widetilde{w} = [\widetilde{w}_1, \widetilde{w}_2, \ldots \widetilde{w}_k]$.

Step 2: Perform the normalization for the objective values $\widetilde{w}(CVS)$ by column along with the formula given in equation (9).

$$\tilde{f}_{\Delta ij} = \left(\frac{l_{ij}}{r_j^{max}}, \frac{m_{ij}}{m_j^{max}}, \frac{r_{ij}}{l_j^{max}} \wedge 1\right) \quad (9)$$

Here, i*j is a triangular fuzzy number $\tilde{f}_{ij} = (l_{ij}, m_{ij}, r_{ij}), i \in (1, 2, , \ldots, S), j \in (1, 2, , \ldots, k)$.Performed the normalization process on the number of fuzzy triangular $\tilde{f}_{ij}$.

Step 3: Get the fuzzy utility matrix in the formula given in equation (10).

$$\tilde{r}_{1j} = \widetilde{w}_j . \tilde{f}_{\Delta ij}, \forall\, i, j \quad (10)$$

Step 4: Find the fuzzy utility matrix by using the ideal solution $\widetilde{M}^*$ That is expanded in the equation (11).

$$\widetilde{M}^* = (\widetilde{M}_{1-}, \widetilde{M}_{2-}, \ldots, \widetilde{M}_{k-}) \quad (11)$$

Where, the variable $\widetilde{M}_{j-}$ is expanded as $\widetilde{M}_{j-} = \widetilde{min}(\tilde{r}_{1j}, \ldots, \tilde{r}_{Sj}), j \in (1,2, \ldots, k)$, the membership function of $\widetilde{M}_{j-}$ is demonstrated by using the formula given in equation (12).

$$\mu_{\widetilde{M}_{j-}}(r) = sup_{r=r_1 \wedge \ \ldots r_S}\, min\left\{\mu_{\tilde{r}_{1j}}(r1), \ldots, \mu_{\tilde{r}_{Sj}}(rS)\right\} \quad (12)$$

Where $(r_1, r_2, \ldots, r_S) \in \mathbb{R}^S$.

Step 5: Find the distance DST_i between the fuzzy solution $(\widetilde{M}^*)$ and the i^th solution.

$$DST_i = \sqrt{\textstyle\sum_{j=1}^{k} d_H(\tilde{r}_{ij}, \widetilde{M}_{j-})^2}\,, \; i \in (1, 2, , \ldots, S) \quad (13)$$

Where DST_i is the fuzzy optimality of the i^th independent variable.

Step 6: Perform the sorting operation over the independent variables based on the variable DST_iValues from least value to the highest value. The independent variable provides the least fuzzy optimality value as the best solution.

The above steps are carried out to find the best solution by using the distance between the fuzzy optimal solution and the other. This fuzzy optimality is used to find the best solution by considering the input data or content. Next, the hummingbird's optimization algorithm is explained by considering the semantic similarity values and fuzzy optimality to identify the best features and terms.

4.3. Hummingbirds Optimization

The Hummingbirds Optimization technique is used in this work for optimizing the text that is optimized by the fuzzy optimality and semantic similarity score. Generally, this optimization technique consists of two phases such as self-searching and guide-searching phases. The hummingbirds are searching the suitable positions for them as a feasible solution. The best food is considered an optimal solution for the search problem. This optimization technique is initialized using the formula in equation (14).

$$POS_i = UPB - RND.(UPB - LPB) \quad (14)$$

Where the variable POS_i indicates the i[th] hummingbird's position in a certain area ($i \in \{1,2,3,\ldots,N\}$, N represents the size of the population), and UPBindicate the upper bound and LPBrepresent the lower bound in the search area, RND represents the random number that is from 0 to 1.

The self-searching process of the hummingbirds is converting the cognitive characteristics into a mathematical model that is treated as the last solution of the current searching process. The hummingbird "i" finds the best food source ($POS_i^t \neq POS_i^{t-1}$)it means that the current search area is further. The new i[th] hummingbird's position is calculated using the formula given in equation (15).

$$POS_i^{t+1} = POS_i^t + RND.(POS_i^t - POS_i^{t-1}) \quad (15)$$

Where, the variables POS_i^t and POS_i^{t+1} are indicating the i[th]positions of the hummingbird at the t iteration and t-1 iteration. The variable POS_i^{t-1} is accepted, then it provides better value, or it is unchanged. The searching process of the i[th] hummingbird failed to find a better result ($POS_i^t = POS_i^{t-1}$) while searching continuously. The hummingbird changed the search direction. The searching procedure is implemented according to the Levy flight, which is an important non-Gaussian random walk [33]. The hummingbirds have generated the new positions by applying Levy flight as explained below:

$$POS_i^{t+1} = POS_i^t + \alpha \oplus LF(\beta) \quad (16)$$

Where the variable αindicates the scale factor which is related to the problem interest, the symbol $\oplus$represents the entry-based multiplications and the variable POS_i^{t+1}provides a better fitness value. The $\alpha$and LF(β)is calculated by using the formula given in the equation (17).

$$\begin{cases} \alpha = \alpha_0(POS_i^t - POS_{best}^t) \\ LF(\beta) = \frac{\mu}{|v|^{1/\beta}} \end{cases} \quad (17)$$

Where the variable POS_{best}^trepresents the solution as best at t iteration and α_0 is a constant. The variables μ and v are chosen from the normal distribution $ND(0,\sigma_\mu^2)$ and $ND(0,\sigma_v^2)$ with $\sigma_\mu = \left(\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right)^{1/\beta}$, $\sigma_\mu = 1$. Here, the variableΓ(z) indicates the Gamma function and the variable $\alpha_0$holds the value of 0.01, and the variable βholds the value of 1.5 in this work.

In this self-searching process, the hummingbirds are learned based on the gradient data that accelerates the method's speed. Even though the method falls into an optimal local solution and the search space of hummingbirds is calculated using LF, that is improved the search capability of the method.

4.4. Proposed Semantic Fuzzy Aware Hummingbirds Optimization Method

The proposed semantic similarity and fuzzy optimality aware hummingbirds optimization method (SFO-HOM) is explained in this section. The SFO-HOM is used to select the optimal key terms that are more relevant and useful for performing effective text classification and document categorization. The hummingbird's searching process is useful for selecting the optimal features or terms that help enhance the classification accuracy. The current position of the bird is similar to the optimal position. The searching process is described in equation (18).

$$POS^{T,t+1} = POS^{T,t} + r_d.\curlywedge \quad (18)$$

Where, the variable $POS^{T,t}$indicates the position of t[th] iteration, the variable $r_d$represents the random value in the range from -1 to 1 that is changed the individual bird's search direction; the symbol$\curlywedge$indicates the scaling factor of the bird moving around the current position. Here, the symbol$\curlywedge$holds the value of 0.1(ub-lb).The variable $POS^{T,t+1}$is replaced by the value of the variable$P^{T,t}$when the fitness value is better than the variable $POS^{T,t}$. The steps of the proposed SFO-HOM are as follows:

Semantic Similarity and Fuzzy Optimality aware Hummingbirds Optimization Method

Input: Text Document
Output: Optimal key terms
Step 1: Set the upper bound, lower bound, number of iterations, and N value.

Step 2: Initialize the population of hummingbirds using the equation (15).

Step 3: Perform the self-searching process for all the iterations.

3.1 if the value of P_i^t is not equal to P_i^{t-1} Then
3.2 Calculate the self-searching value for the specific iteration using the formula

$POS_i^{t+1} = POS_i^t + RND.(POS_i^t - POS_i^{t-1})$;

3.3 Else
3.4 Find the self-searching value using $POS_i^{t+1} = POS_i^t + \alpha \oplus LF(\beta)$ for the current iteration.
3.5 End if
3.6 Check the boundary value and calculate the fitness value for the POS_i^{t+1}.
3.7 Initialize the value of POS_i^{t+1} to POSi.

Step 4: Perform the guide-searching process for the bird.

4.1 Initialize the value of $POS^{T,t} + r_d.\curlywedge$ into $POS^{T,t+1}$.

4.2 Find the fitness value for the $POS^{T,t+1}$by checking the boundary value.

4.3 Initialize the value of $POS^{T,t+1}$ into POS^{T}.

4.4 Find the PF[t]using the formula$PF^{t} = \frac{rank(fitP^{F,t})}{N-1}$

Step 5: for j = 1 to N -1 do

5.1 ifthe value of$POS^{F,t}$is greater than POS^{T} then

5.2 $POS_j^{F,t+1} = POS_j^{F,t} + RND.(POS^{F,t} - MF.POS_j^{F,t})$

5.3 else

5.4 $POS_j^{F,t+1} = POS_j^{F,t} + RND.(POS^{F,t} - POS_j^{F,t})$

5.5 Check the value of fit.$POS_k^{F,t}$is greater than the value of$fit.POS_j^{F,t}$\

5.6 Assign the values of $POS_j^{F,t} - RND.(POS^{F,t} - POS_j^{F,t})$ in to $POS_j^{F,t+1}$.

5.7 Otherwise, check the boundary and also find the fitness value for the position $POS_j^{F,t}$.

5.8 Assign the value of $POS_j^{F,t+1}$ into POS^{F}.

Step 6: if POS(BIRD) > BIRD, Then

Apply the mechanism for changing the role

Step 7: Next iteration

Step 8: Provide the Best Optimized Terms

The proposed SFO-HOM is applied in this work for selecting the more relevant key terms that are helpful to identify the more relevant and useful study materials.

4.5. RoBERTa

The Robustly Optimized BERT Pre-training Approach (RoBERTa) has been developed by Liu et al. (2019), which is the extended version of the BERT model. The various issues of BERTmodel were identified by Facebook AI Research (FAIR), and an optimized and robust version of BERT was built. Generally, the RoBERTa model is used to train the huge datasets and improves the end-task accuracy compared with the standard BERT. Moreover, a new dynamic masking pattern is introduced in RoBERTaand identifies the duplicates by performing the training process. The various masking methods are applied in all the attempts while passing the data. The static masking method is applied for performing the data pre-processing. The text classification works by using the RoBERTa model. This work applies RoBERTa for categorizing the text/document according to the e-learners' interests and learning capability. Roberta also handles the subject materials effectively to recommend suitable study materials useful for learning the subject effectively. In this RoBERTa, the semantic similarity score is considered as additional weightage for the inputs to make an effective decision on input contents and categorize them according to the requirements.

5. Results and Discussion

This section describes the experimental setup, evaluation metrics, and experimental results in detail. Here, the standard datasets were used for validating the performance of the proposed content recommendation system. This work has been implemented using Python Programming Language and Kera's TensorFlow in a Personal Computer with an Intel i7 2.3 GHZ core processor with a minimum of 8 GB RAM. The various subject contents are used as input. The Amazon dataset, which contains review comments on various products, is also used to conduct experiments and evaluate the proposed content recommendation system. First, this section explains the evaluation metrics.

5.1. Evaluation Metrics

This subsection is explained the three-evaluation metrics, such as precision, recall, and f-measure, that help evaluate the performance of the proposed content recommendation system. Moreover, the prediction accuracy is calculated using the proposed content recommendation system's precision, recall, and f-measure values. The precision value (PV), recall value (RV), and f-measure value (FV) are calculated by using the formulae that are given in equations (19). (20) and (21).

$$PV = \frac{No.of\ more\ relevant\ documents}{Total\ no.of\ documents\ considered} \quad (19)$$

$$RV = \frac{Total\ no.of\ relevant\ document\ retrieved}{Total\ no.of\ documents\ retriueved\ from\ repository} \quad (20)$$

$$FV = 2 \times \frac{PV \times RV}{PV + RV} \quad (21)$$

The proposed content recommendation system is evaluated using parameters such as PV, RV, and FV. The experiments have been conducted to evaluate the proposed content recommendation system. Here, the content similarity is considered for identifying the suitable content using the mentioned evaluation parameters. Moreover, the prediction accuracy (PA) is calculated using the values such as PV, RV, and FV presented in the equation (22).

$$PA = \frac{PV + RV}{FV} \quad (22)$$

Generally, the prediction accuracy is an important factor for identifying whether the content recommendation system is efficient and performing the comparative analysis.

5.2. Experimental Results

This section proved that the performance of the newly developed content recommendation system is superior to the available systems. The proposed system is proved in all experiments by considering the precision, recall, and f-measure values. First, the proposed system is proved as superior to the available systems that LSTM proposes, Sankar et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021), according to the precision value which is shown in figure 2. Here, five experiments have been conducted considering the different sets of relevant documents for user requests. These five experiments also considered the different numbers of documents, such as 100, 200 documents, 300 documents, 400 documents, and 500 documents. All these documents are collected from the internet and local repositories for different subjects such as Software Engineering, Computer Networks, Machine Learning, Deep Learning, Big Data Analytics, Object Oriented Programming, Java Programming, Python Programming, Artificial Intelligence, and Soft Computing. All the content levels, from basic to advanced concepts, were considered for conducting experiments in this work.

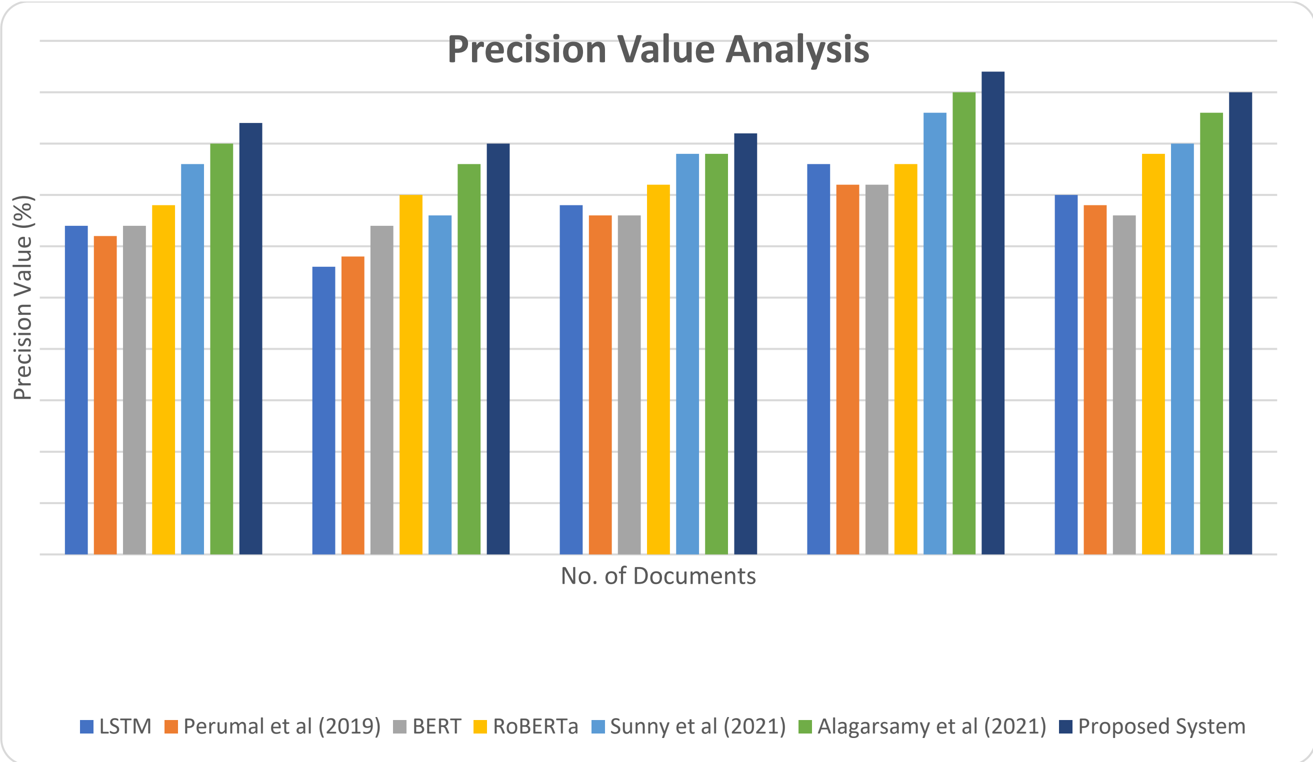

Fig. 2 Precision Value Analysis

Figure 2 shows five experimental results considering various documents such as 100, 200, 300, 400, and 500. The proposed system achieved better precision value than the existing systems such as LSTM, Sankar et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021). The enhancement is the incorporation of the newly proposed SFO-HOM with the combination of Semantic Similarity Score, Fuzzy Optimality, and Hummingbirds Optimization Algorithm and RoBERTa.

Second, the proposed content recommendation system is proved as better than the existing systems such as LSTM, Perumal et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021), according to the precision value which is shown in figure 3. Here, five experiments have been conducted considering the different sets of relevant documents for user requests. These five experiments also considered the different numbers of documents, such as 100, 200 documents, 300 documents, 400 documents, and 500 documents. All these documents are collected from the internet and local repositories for different subjects such as Software Engineering, Computer Networks, Machine Learning, Deep Learning, Big Data Analytics, Object Oriented Programming, Java Programming, Python Programming, Artificial Intelligence, and Soft Computing. All the content levels, from basic to advanced concepts, were considered for conducting experiments in this work.

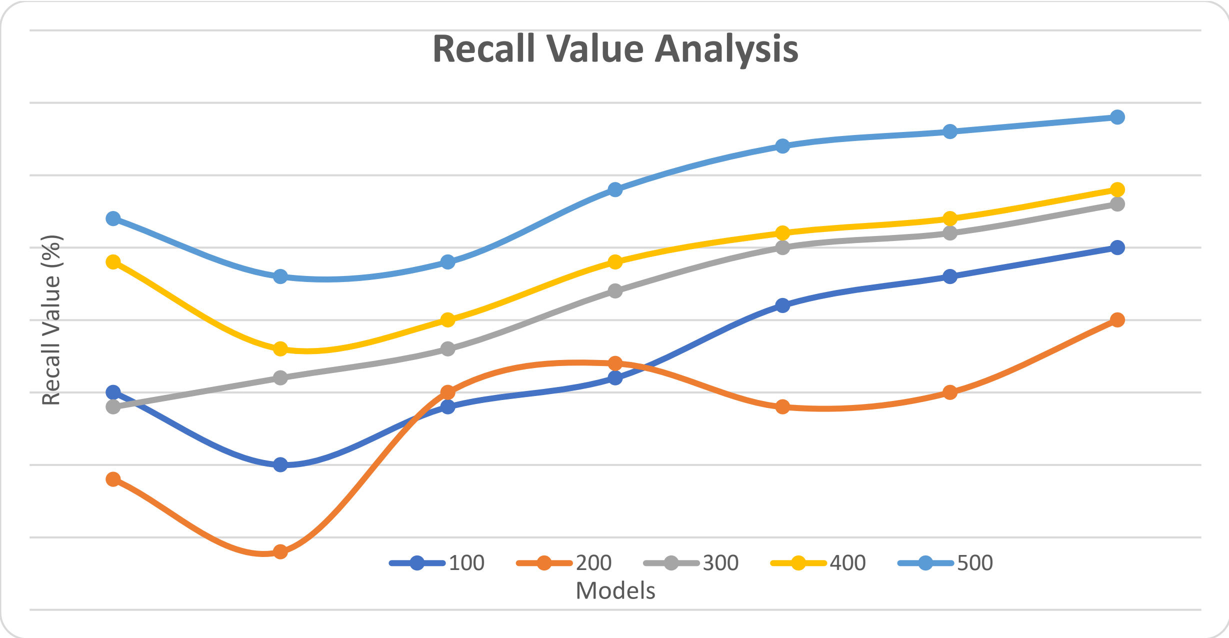

Fig. 3 Recall Value Analysis

The proposed content recommendation system is better than the existing systems in figure 3, which has five experimental results considering different documents such as 100, 200, 300, 400, and 500. The proposed system achieved better recall value than the existing systems such as LSTM, Perumal et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021). The enhancement is the incorporation of the newly proposed SFO-HOM with the combination of Semantic Similarity Score, Fuzzy Optimality and Hummingbirds Optimization Algorithm, and the Semantic Similarity aware RoBERTa.

Third, the proposed system is proved as better than the existing systems such asLSTM, Perumal et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021), according to the F-Measure value which is shown in figure 4. Here, five experiments have been conducted considering the different sets of relevant documents for user requests. These five experiments also considered the different numbers of documents, such as 100, 200 documents, 300 documents, 400 documents, and 500 documents. All these documents are collected from the internet and local repositories for different subjects such as Software Engineering, Computer Networks, Machine Learning, Deep Learning, Big Data Analytics, Object Oriented Programming, Java Programming, Python Programming, Artificial Intelligence, and Soft Computing. All the content levels, from basic to advanced concepts, were considered for conducting experiments in this work.

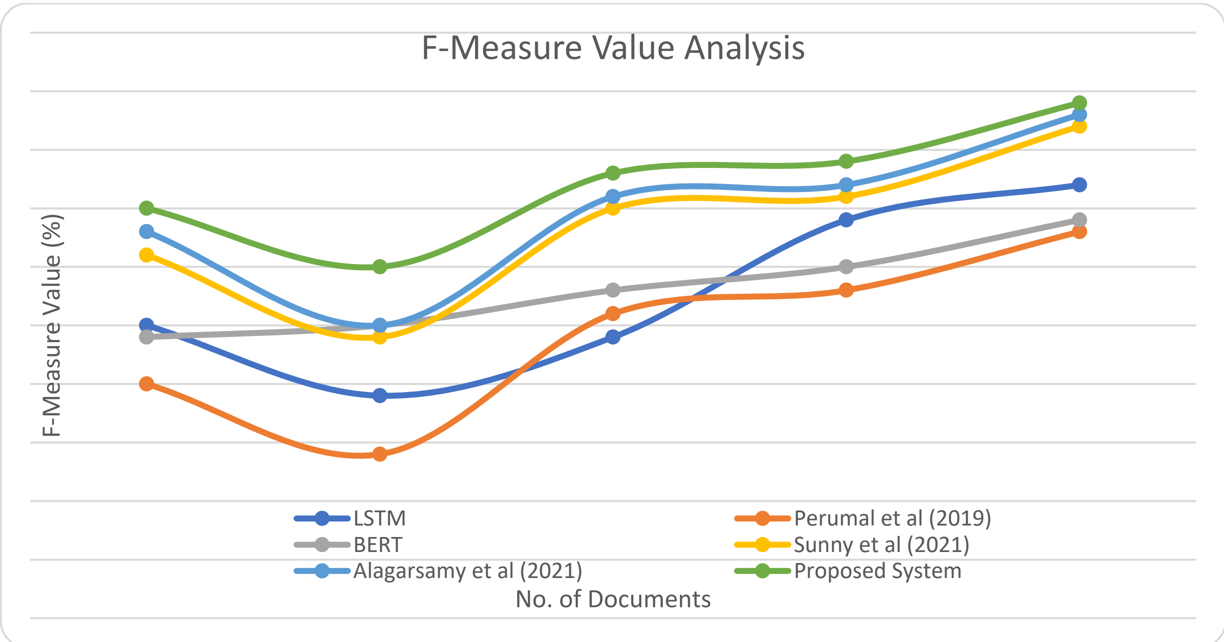

Fig. 4 F-Measure Value Analysis

The proposed content recommendation system is better than the existing systems in figure 4, which has five experimental results considering different documents such as 100, 200, 300, 400, and 500. The proposed system achieved better precision value than the existing systems such as LSTM, Perumal et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021). The enhancement incorporates the newly proposed SFO-HOM with the combination of Semantic Similarity Score, Fuzzy Optimality and Hummingbirds Optimization Algorithm, and the semantic similarity score aware weighted RoBERTa.

The content relevancy is measured by considering the similarity value between the relevant contents of the documents. Figure 5 shows the content similarity analysis between the proposed content recommendation system and the existing content recommendation systems such as LSTM, Perumal et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021). Here, five experiments have been conducted considering various sets of relevant documents. Randomly 100 documents were selected and conducted the experiment 1, 200 documents were selected randomly and conducted the experiment 2, 300 documents were selected randomly and conducted the experiment 3, 400 relevant documents were selected and conducted the experiment 4 and experiment 5 was conducted with 500 relevant documents that are selected randomly.

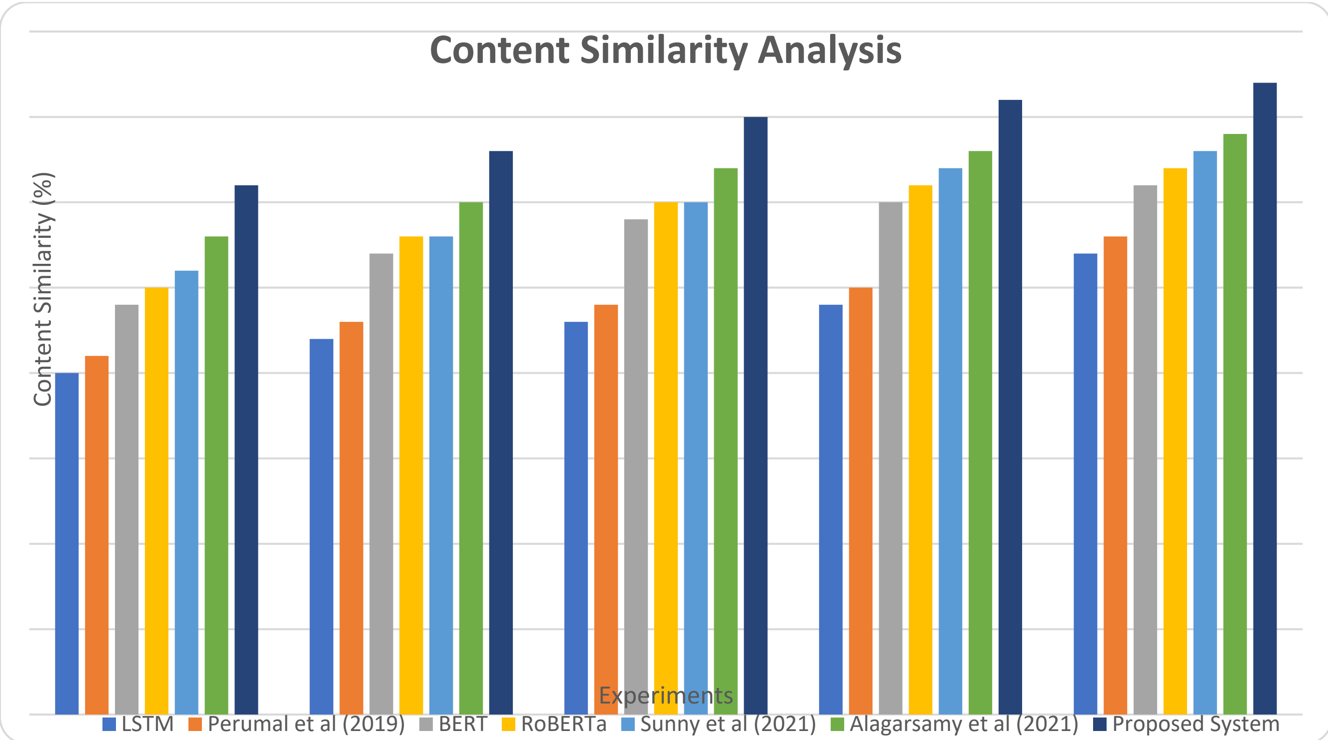

Fig. 5 Content Similarity Analysis

The content similarity between the relevant contents is considered for conducting content similarity analysis. Figure 5 proved the efficiency of the proposed content recommendation system as better than the existing recommendation systems such as LSTM, Perumal et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021) in terms of content similarity finding accuracy. It is because the application of newly proposed algorithms, namely Semantic Similarity, and Fuzzy Optimality, is aware of Hummingbirds Optimization Method and the semantic weight considered RoBERTa.

Table 1 shows the overall performance of the proposed content recommendation system according to the precision value, recall value, f-measure value, and prediction accuracy. Here, the average results of all the performance metrics have been considered for performing a comparative analysis between the proposed content recommendation system and the existing systems such as LSTM, Perumal et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021). Five experiments have been conducted and calculate the average performance of the proposed and existing systems in terms of precision value, recall value, f-measure value and prediction accuracy for comparative analysis. The various set of documents that are selected randomly is used for conducting experiments.

Table 1. Performance Comparative Analysis

Content Recommendation Systems	Precision Value (%)	Recall Value (%)	F-Measure Value (%)	Prediction Accuracy (%)
LSTM	92.29	93.17	94.07	93.52
Perumal et al 2019	98.51	97.79	98.75	98.73
BERT	98.42	98.31	98.84	98.78
RoBERTa	98.62	98.51	99.05	98.98
Sunny et al 2021	98.72	98.42	98.87	98.65
Alagarsamy et al 2021	98.63	98.56	98.92	98.92
Proposed System	99.42	99.67	99.88	99.77

Table 1 proves the efficiency and effectiveness of the proposed content recommendation system based on the precision, recall, f-measure, and prediction accuracy. Here, the proposed system performance is superior to all the recommendation systems in all the performance metrics considered in this analysis. The reason for the enhancement is the use of the proposed feature optimization method, which considered the Semantic Similarity Score, Fuzzy Optimality, and Hummingbirds Optimization Algorithm for effective feature optimization and the existing RoBERTa with the consideration of semantic similarity score.

Table 2 shows the recommendation accuracy for the proposed system according to the number of user requests and their relevant documents. Here, the recommendation accuracy analysis is made between the proposed system and the existing recommendation systems such as LSTM, Perumal et al. (2019), BERT, RoBERTa, Sunny, et al. (2021), and Alagarsamy et al. (2021). Here, different queries have been obtained from different fields interested users' requests for obtaining suitable documents for enhancing their knowledge in their areas and learning in depth. Moreover, different queries such as 50, 100, 150, 200 and 250 are considered the best relevant documents for performing analysis.

Table 2. Recommendation Accuracy Analysis

No. of Requests	No. of related documents	LSTM	BERT	RoBERTa	Sunny et al 2021	Proposed System
50	100	93.52	98.78	98.92	98.75	99.72
100	200	93.55	98.79	98.94	98.78	99.74
150	300	93.58	98.82	98.96	98.81	99.77
200	400	93.62	98.84	98.98	98.85	99.79
250	500	93.65	98.87	99.02	98.89	99.83

Table 2. Recommendation Accuracy Analysis w.r.t users' requests and relevant documents Here, the proposed content recommendation system achieved around 1% improvement in prediction accuracy when considering the different numbers of requests such as 50, 100, 150, 200, and 250 and the different numbers of related documents such as 100, 200, 300, 400 and 500. Here, the proposed system's prediction accuracy is superior to all the existing recommendation systems when considering the different requests and the number of related documents in this analysis. The reason for the enhancement is the use of the proposed Semantic Similarity and Fuzzy Optimality aware Hummingbirds Optimization Method (SFO-HOM), and the weighted RoBERTa with semantic similarity helps enhance the performance of the proposed content recommendation system. Here, the weight is assigned with input data on RoBERTa.

6. Conclusion and Future Work

A new content recommendation system has been proposed and implemented by applying the newly proposed semantic fuzzy optimality aware hummingbirds optimization method and standard RoBERTa for identifying the more relevant content to the e-learners according to their interests, needs, and learning capability. In this work, a semantic similarity score calculation methodology is used for calculating the semantic similarity score, which helps categorize the study material. Moreover, the existing fuzzy optimality method is also considered for feature optimization. In addition, the hummingbirds' optimization method has used the output of the semantic similarity score and the fuzzy optimality. Finally, a feature optimization process helps enhance the content recommendation process. Finally, the RoBERTa is applied for categorizing the relevant, irrelevant, and most useful documents from the available online, local repository, and dataset. Based on the result, the relevant contents are recommended for the learners as suitable documents. The proposed content recommendation system is proven better than the existing system in terms of precision, recall, f1-measure, and prediction accuracy. This work will be improved further with the new lightweight feature optimizer and the improved deep learning algorithm.

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