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# INTERACTIVE EDUCATIONAL SYSTEM USING ARTIFICIAL INTELLIGENCE TECHNIQUE FOR THE HIGHER EDUCATION SYSTEM

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**ABSTRACT**

Artificial Intelligence (AI) has often made meaningful participation in the higher education system. AI has often helped both educators and teachers create interactive sessions. Teachers still do not know how to use this pedagogically in a broader range, which can have a constructive impact on subsequent knowledge and training. Therefore, in this paper, an Artificial Intelligence-based Interactive Educational System (AI-IES) has been proposed to enhance students' interactive sessions for higher education. The AI configurations assure a considerable enhancement of teaching and learning improvements in quality. The IES model helps teachers precisely customize the teaching according to their requirements and integrate the various forms of human social interaction and Information and Communication Technology. IES made an in-depth assessment to describe and illustrate an interactive educational system's position in learning and evaluate the different research innovations conducted worldwide following the educational system's AI techniques. The experimental results suggest that AI-IES achieves the highest performance rate compared to other existing methods.

**KEYWORDS:** Artificial Intelligence, Information and Communication Technology, Students

## 1. Education 5.0

To change the structure of the education system, so it suits the development of technology by robotics and artificial intelligence and to achieve an even better Education 5.0 paradigm aimed at solving challenges and generating value, all stakeholders such as professionals, political officials, educators, and students have to make a huge effort [1-2]. Simply listening and taking notes is not learning. Nowadays, educators are massively shifting to interactive teaching methodologies [3-4]. Learners and teachers are the primary active participants in technological research through interactive teaching, which automatically results in creativity and entrepreneurial thinking [5]. Interactive learning encourages experimentation mechanisms that instill the potential and development of the student's professional identity through their thought like experts. The ultimate responsibility of translating traditional students into productive learners lies primarily on the teachers [6-7]. The teacher's role is to be the leading force or tutor rather than the imparting of information in this purely results-based education. Online interaction demands the individuality of the teacher's behavior, teaching abilities, and skills, and this master class is exactly about what these skills are and how to improve them [8-9]. The techniques that have been learned during the sessions will help the learners address certain barriers to online education and create a diverse atmosphere for teaching. Information and communication technologies (ICT) plays an important role in their innovations [10].

Technological innovations through ICT help teachers efficiently and creatively while empowering students to develop critical thinking skills. It allows students to study more easily, flexibly, and safely, exponentially increasing and influencing nearly all higher education aspects [11-12]. Education and learning through ICT include computer-aided learning, web teaching, computer courses, online training, distance education, e-learning, interactive learning, digital training etc. Offering unrestricted access to classes, programs, and pedagogical methods that are not accessible geographically, an expansion of the open educational tools trend has increased [13]. The innovative ideas can lead students through personalized learning pathways, recognize appropriate learning materials, provide interactive learning opportunities, and provide insight and support beyond the defined engagement cycle. ICT is arranged according to the objective, intent, and field of application in various courses. In intelligent learning, monitoring, and efficiency of the learning process are critical [14]. An intelligent learning system represents digitalized schooling, which has received further coverage. Smaller, smarter, and more cost-effective computers are being online education. Now many graduates or learners use smart and digital electronic devices in their daily lives to communicate, study, and entertain. In addition, with the advent of Smart Education, additional technology, such as cloud, learning analysis, Big Data, Internet of Things (IoT), and wearable technologies [15-16].

In education 5.0, artificial intelligence (AI) plays a vital role. AI-based tools and bots can help teachers recognize their students' success and failure generators and follow a customized student model based on their knowledge level, integrate learning systems, including statistical models with learning algorithms, and even track students' development throughout their curriculum [17-18]. Smart sensors and wearable devices improve learning analysis with contextual information, which combines interactive learning activities with sensor data acquired in real-time [19-20]. New generations of students have been produced with ready-to-use availability for digital platforms and can use computerized learning resources quickly and conveniently. The online or interactive resources help students better 'self-exploring, enrich their learning experience, and inspire them to tweak things with equations to create interesting graphics or animations [21]. This promotes a better comprehension of abstract deductions or mathematical terms in the classroom. Examples of student reviews and additional work used in the curriculum are obtained in the application of this content in both the graduate course and postgraduate classroom [22-24].

The aim of this document thus defines the Artificial Intelligence-based Interactive Educational System (AI-IES) to improve the interactive student session for higher education. AI modules significantly increase the efficiency of teaching and learning. The proposed AI-IES model enables teachers to tailor the instruction according to their needs and incorporate diverse modes of human social activity and ICTs. The AI algorithm in the proposed system carries a detailed evaluation of the digital learning environment and compares it with the various research innovations made worldwide according to AI technology in the educational system.

The remaining section contains the major innovative interactive education models and the learning assessment frameworks. Following this, a detailed explanation of the proposed AI-IES design is given. The result and discussion finally include the experimental findings with significant charts and tables. At the end of this paper, the conclusion and the future scope.

## 2. Existing Models

This section includes some of the major interactive education systems or approaches proposed from 2018 to 2020. The following gives the summarized report of those research works.

Defu Bao et al. [25] developed and proved the feasibility of interaction in online education and the online model of assessment of the interaction between professors, students, and machines. In online education, the interactive connection was applied through online education media, and the engagement in the current online teachings was evaluated via the establishment and quantification of the online assessment database. The validity of the interactions and the index system was analyzed.

Jing Wei et al. [26] presented an open collaborative learning algorithm based on cloud computing and Big Data. The proposed approach increased the scheduling and identification of educational services and enabled the effective exchange of resources. They showed that the proposed approach had several benefits relative to the existing models; however, the implementation procedure was complicated. They selected data from several participatory research to ensure the consistency of the findings during the experiment.

An interactive 3D education system was developed by S. Kang et al. [27] which built a rebar work process and assessed the performance and satisfaction of the students. Portable Interactive Education for Construction Engineering in 3D (PIECE-3D) had outperformed portability in conjunction with the current Building Information Modelling (BIM) teaching model and has brought instructional targets in 3D, improved awareness of rebar processes and aroused student interest

Fei Kong et al. [28] designed an interactive English teaching environment based on an interactive human-computer and a backpropagation neural network. They addressed the computer-based multimedia English teaching model. The building of knowledge was applied to the transition of knowledge, which would be the key subject of knowledge ownership or adoption, including the consolidation of knowledge and applying knowledge on three linkages. They claimed that their proposed English language education framework would be a network update e-learning portal.

Syed Ali Hassan et al. [29] discussed childhood education using a game-based Augmented Reality (AR) platform. The AR Game offered children tasks and instructions to fulfill them in due course. They concentrated more on an easy and efficient way to understand and memorize their activities for the children. Their proposal could assist children in engaging in a picture destination with computer-generated vehicles, houses, and other 3D objects. They taught the children how to understand simple names, parking spaces, how to orthodoxy, drive a handheld joystick car, and see it in reality.

The extended literature survey finds a research gap between interactive education systems and the evaluation model. Therefore, this study presents an Artificial Intelligence-based Interactive Educational System (AI-IES) with real-time performance assessment. The AI modules in the proposed system can ensure major changes in the standards of education and learning. The IES model can assist online teachers in adapting their instruction to their needs and integrating the many ways of social contact with human beings and information & communication technology. A comprehensive evaluation has been carried out by IES to identify and explain the role of an immersive education method in learning and compare the various developments in a worldwide study based on the AI techniques of the education system. The following explains in detail.

## 3. Artificial Intelligence-based Interactive Educational System

An interactive education system can be termed as the pedagogical approach to course design and implementation that combines online communities and cloud computing technologies. The hyper-growth in the use of digital technology and virtual communication, especially by students, has given rise to interactive learning. Computer-based instructional materials are mapped onto an Interactive Touch-Screen or other devices. The users of the interactive learning system can communicate with the information on the device by touching, selecting, dragging, and manipulating it. This is because the students are stepping into one of the thousands of learning environments that have been animated and shown on the monitor. Teachers reinforce and improve lessons in an immersive classroom environment. Students must have an easier time mastering the main learning outcomes because the content is engaging and enjoyable. Comprehensive teacher and student support resources and instructional events are available to go along with the software programs.

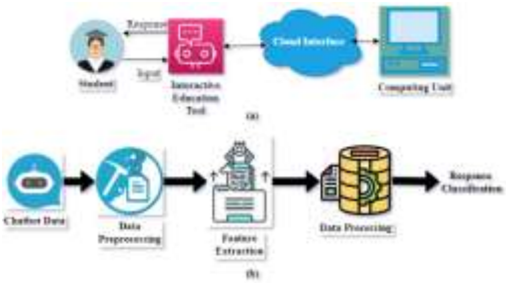


**Figure 1: Artificial Intelligence-based Interactive Education System (a) Conceptual Diagram (b) Computation Flow**

Figure 1(a) shows the conceptual diagram of the proposed AI-IES model, where student-teacher communication and interactive learning have been implemented through a chatbot designed in this research. The designed chatbot for interactive learning/education has been integrated with the cloud service, where the communication or interaction data have been stored and managed. The cloud data can be retrieved at the computing unit, where the data preprocessing, feature extraction, and data processing occur, as shown in Figure 1b. The computing unit results in the performance evaluation outcomes labeled as positive, negative, and neutral. The data preprocessing module performs tokenization, stop-word removal, and punctuation removal, etc. The feature extraction can be achieved using the method named Term frequency-inverse document frequency (TF-IDF). The extracted features were then applied to the classification module, where the student performance in terms of response type (Positive, Negative, and Neutral). This study evaluates the AI-IES performance by performing simulation research using the chatbot datasets available on the internet.

### 3.1. Interactive Education Tool (Chatbot) Design

The interactive education tool (chatbot) design phase has two modules, including the Questionnaire Generation module and Query/Response. This interactive education tool can import course materials that go through a series of preprocessing steps before being translated into an information base that these two modules use as data. Apache PDFBox, an open-source Java application, has been used to translate the document from portable document format (PDF) to text format. The text document can be used as the input to natural language preprocessing to remove redundant sentences and enforce context awareness.

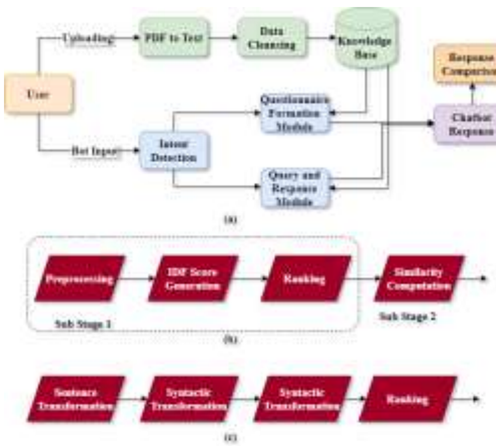


**Figure 2: Interactive Education Tool (Chatbot) Design (a) Module Wise Structure (b) Phase 1: Query and Response (c) Phase 2: Questionnaire Formation**

Figure 2 gives the generic flow of information or data from chatbot users to get the chatbot responses and thereby for evaluation. Figure 2a and figure 2b give the block diagram of query and response and questionnaire formulation modules. The proposed chatbot imitates the student-teacher interaction or conversation through voice commands and text chats. The intelligent tutoring programs that offer students customized learning environments have grown as the field of natural language processing (NLP) increasingly evolved. The Query and Response and Questionnaire Formation chatbot allows the user to upload the most relevant documents or tutorial resources to which two main tasks, answer extraction and question generation, are conducted after the documents have been translated to a suitable knowledge base. Phase 1 extracts valid answers from the knowledge base using ranking functions, then feeds the top R answers to a neural network, which selects the final answer. Phase 2 uses a variety of ranking mechanisms to rate sentences according to their relevance to the document's subject matter. These sentences are then passed through an NLP transformation unit before actually being used for creating questions, which then get filtered and posed to the user as a questionnaire. The Response Comparison module collects the user's answers to the questions and measures the questionnaire score. The suggested method is more suitable for subjects that need analytic or statistical knowledge than for subjects that require factual information. The following gives the statistical description of the two phases shown in Figure 2b and Figure 2c.

#### 3.1.1. Phase 1: Query and Response

In the query and response phase, the chatbot takes the user's question as input and utilizes the generated knowledge base to extract the most suitable response sentence to deliver it as a chatbot response. This phase has two sub-stages. Substage 1 includes text preprocessing, IDF score generation (dictionary), and ranking function. Whereas substage 2 includes a similar score computation module. Tokenization, singularization, lemmatization, and punctuation elimination are all implemented in every response sentence from the generated knowledge base and the student query. Tokenization in the preprocessing stage replaces the sensitive data with specific identity symbols that preserve any of the data's important details without jeopardizing confidentiality. This concept of extended tokenization splits strings into simple processing units and interprets and groups isolated tokens to form higher-level tokens. Pre-processed texts are segmented into textual units. The first operation of this module is to transform the text to word counts, which is the same as a bag of words, and then to delete any void sequences through cleansing and filtering. Finally, a set of features known as tokens, sentences, phrases, or attributes have been formed by breaking each input text document. This preprocessing thus performs lexical normalization such as stemming, singularization, and lemmatization.

$$IDF(W) = \log_e \frac{0.5+M-F(W)}{0.5+F(W)} \quad (1)$$

$$S^{+} = \frac{F(W)*IDF(W)*(\partial+1)}{F(W)+\partial*(1-\delta+(\delta*\frac{L_s}{Avg\,L_s})} \quad (2)$$

After preprocessing, the pre-processed data has been used to perform the IDF score dictionary generation, where each text data can be taken as the document. The IDF score function thus computes the score value for each word in the pre-processed document, as expressed in equation 1. The IDF score obtained from the function $IDF(W)$ results for each word in the preprocessed data. The $M$ denotes the total number of words in the preprocessed document. This score computation extends with the best matching algorithm BM25, as denoted in equation 2.

**Figure 3: Path Diagram of IDF function for Getting the Preprocessed Data**

The parameters $\partial$ and $\delta$ are the constants and are defined at the beginning of the data processing. The $L_s$ and $Avg\ L_s$ determines the length of the sentence inputted and the average sentence length among multiple sentences inputted by the chatbot user, respectively. The path diagram for equation 2 is illustrated in Figure 3. The IDF function can compute a score value based on the document frequency of a word, which is the number of documents containing the word. For each word in the query, this value is compounded by the TF(W) element, and the products are then added to form the document's initial ranking.

$$RF=\alpha-\beta*\log_e \frac{10+(P_W-1)/20}{10+L_s/20} \tag{3}$$

The third submodule of sub-stage 1 is the computation of rank using the ranking function, as expressed in equation 3. The $RF$ denotes the ranking function, which results in the rank of the selected word positioned at $P_W$The parameters $\alpha$ and $\beta$ are the constant parameters similar to those used in finding the score value, as shown in equation 2. In substage 2, the similarity computation has been performed through the neural network.

$$LF=\sum_{j=1}^{\partial} \max\left[ (0,1)-(E_Q-P_R)^T*\omega*(E_Q\odot P_R)+(E_Q-N_R)^T*\omega*(E_Q\odot N_R)\right] \tag{4}$$

$$\omega\Leftarrow\omega+\sum_{j=1}^{\partial} l_r*(E_Q\odot P_R)*(E_Q-P_R)^T-(E_Q\odot N_R)*(E_Q-N_R)^T \tag{5}$$

$$final_{score}=(E_Q-R)^T*\omega*(E_Q\odot R) \tag{6}$$

To choose the most appropriate response sentence, the top ten response sentences have been fed into a machine learning model, feed-forward neural network. Feedforward neural networks, like deep learning algorithms, are trained with gradient-based learning. In this learning process, algorithms such as stochastic gradient descent are used to minimize the cost function. The Doc2Vec representations of the queries and the responses in the dataset are translated. The loss function in equation 4 is reduced to train the neural network. Equation 5 is used to update the weight matrix. Equation 6 is used to calculate the similarity score between the question and the passage. The $LF$ represents the loss function and $E_Q$ and $P_R$ denotes the query embedding and the positive response or correct answer, respectively. The variable $\omega$ defines the weight matrix of the feed-forward neural network. The $(E_Q-P_R)^T$ results in the transpose matrix of the query and positive response relation. Similarly, respective operations have been used with negative response or wrong answer $N_R$ for the query $E_Q$. The variable $l_r$ takes the value of learning rate to be selected randomly for the neural network training. Finally, the $final_{score}$ determines the similarity score between the query and response.

#### 3.1.2. Phase 2: Questionnaire Formation

In this phase, the chatbot questions and questionnaires have been generated. This phase is thus classified as two sub-stages comprising developing queries from a given input document, choosing a series of questions (questionnaires) for the quiz from those available, collecting student responses, and measuring questionnaire/quiz results after the responses have been passed through the final response comparison module. Sub-stage 1, named query formation, can take the pre-processed document as the input and transformed it into the previously used knowledge base. A set of ranking functions have been used to extract the top 100 sentences from chatbot generated possible sentences and fed into a query recommendation method, which produces a set of question-answer pairs with the desired sentence as the answer and a Wh-question as the corresponding question for each pair. Until being processed for retrieval for the questionnaire, these pairs are further filtered.

Sentence extraction is the first step in this procedure. The questions considered in this study respective to the chosen subject are those that fall into the sixth tier (remembering) of Bloom's taxonomy, which is a model for describing educational learning goals and categorizing them into various grades of difficulty. Identifying, highlighting, explaining, recalling, labelling, and locating information are all ways of remembering. This study mainly focuses on the questions in the type of "remembering" concerns, and thereby generating response sentences from the tutorials/textbooks should be evidence-based — for example, each question must have a true fact as its main subject. This research recognizes main sentences and just uses them to produce quiz questions. As seen in the preceding phase and often a set of scoring functions, a collection of preprocessing steps is used to accomplish this. Sentences of the textbook or tutorial-related terms like "Book," "Chapter," "Practice," and so on are excluded. Such exclusions in this model achieved as part of the general preprocessing phase to remove the likelihood of irrelevant questions, including, "What can you see in the specified figure?".

To define the key sentences in the textbook, various standards are used to rate the sentences. The word scoring approach, which is based on uppercase, word frequency, proper nouns, and TF-IDF. Whereas the sentence scoring approach, takes into account the existence of sentence form, sentence length, and numerical results. Another approach of graph-based scoring, involves the most significant TextRank algorithm. These scoring measures are used, with the exception of the sentence length factor, which is used as described in Equations 7 and 8. To increase the efficiency and time of the training datasets, TF-IDF decreases the dimensionality of the derived features and transforms text to numbers.

$$TF\_IDF(W,D)=TF(W,D)*IDF(W,D) \quad (7a)$$

$$IDF(W,D)=\log\frac{N_D+1}{1+DF(W,D)} \quad (7b)$$

The number of times the term or features $W$ appear in $D$ documents or conversations can be expressed as $TF(W,D)$, even though the frequency of the term or features $W$ appear in all documents or all conversations becomes $IDF(W,D)$. In equation 7a, the $TF\_IDF(W,D)$ measure the TF-IDF score for term $W$ in document $D$, where $N_D$ corresponds to a document's sum in the training dataset and derived from equation 7b.

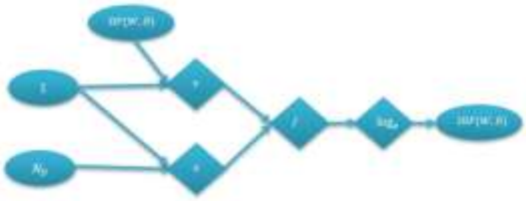

**Figure 4: Path Diagram for computing *IDF*(*W*,*D*)**

In equation 7a and 7b, the variable $TF\_IDF(W,D)$ is the method used to perform the preprocessing in sentence scoring, which determines the frequency of the word $W$ occurrences in the document $D$ and converts the text into numbers. The path diagram for the computation of the inverse document frequency of the word in the pre-processed documents is illustrated in figure 4.

$$SW(n_j)=\rho*\sum_{n_k\epsilon Adj(n_j)}\frac{S_{jk}}{\sum_{n_i\epsilon Adj(n_k)}S_{ki}}SW(n_k)+(1-\rho) \quad (8)$$

Next, the TextRank algorithm generates a graph form of the document, with the edge between two nodes ($n1$ *and* $n2$) representing the semantic relationship between two words. Then, on the graph, add PageRank to get the ranking scores for each word. The significance of a word $SW(n_i)$, according to TextRank, has been determined by the importance of the words that relate to it. The variable $S_{jk}$ is the similarity value of the two words represented in terms of nodes $n_j$ and $n_k$. The damping factor $\rho$ is set to 0.85 in equation 8. The function $Adj(n_j)$ can be resulted in the word closely connected to the next word.

$$SL=\frac{1}{|N_S-Avg_{N_W}+C|} \quad (9)$$

Apart from the sentence length factor, which is used as defined in Equation 9, these scoring methods are used. In equation 9, the sentence length factor has been denoted by $SL$. The parameter $N_S$ represents the number of sentences in the document and the variable $Avg_{N_W}$ denotes the average number of words in these sentences. The constant variable $C$ is added as the minimal factor to prevent the division by 0.

$$TScore=TR^{\varepsilon 1}*ToS*SL^{\varepsilon 2}*[w_1*IDF(W,D)+w_2*TF\_IDF(W,D)+w_3*UC+w_4*pNW+w_5*NW] \quad (10)$$

After that, all of the sentence length factor ratings have been normalized from 0 to 1. The $TScore$, represents the final total score obtained for each sentence has been calculated using Equation 10, following the computation of these scores for all of the sentences in document D. The variable $TR$ gives the TextRank value with its exponent $\varepsilon 1$. $ToS$ and $SL$ give the type of sentences and their length, respectively. The sentence length takes the power of exponent $\varepsilon 2$. The variables $UC$, $pNW$ and $NW$ are the upper case words, proper noun words, and numeric word, accordingly. Whereas the variables $w_1$ to $w_5$ are the weights of the various score.

The sentences ranked from 1 to 100, as determined by Equation 10, are fed into the query formation system that is stated earlier in this sub-section. For each sentence, the query formation scheme produces a series of Wh queries, in which either the sentence is the expected answer or sentence comprises of the relevant answer. One query is chosen from this group of questions. The questionnaire formation method returns these question-answer pairs have been filtered depending on the query length versus the response length for each target sentence. If the question is less than half as long as the response, there seems to be a fair chance it doesn't have enough information to respond to. As a result, those pairs are eliminated even more. This elimination can limit the number of questions that are ambiguous. The questionnaire creation step is the process of obtaining access to the generated question-answer pairs and introducing them to the customer. In advanced programs, the quiz can be built based on the difficulty level of the questions if they are saved with a grade. The user must answer each question shown by the chatbot before moving on to the next question in the questionnaire. The response compare module is in charge of measuring the score for each question after the user has completed it. Cosine similarity has been used to find an exact match between consumer and predicted responses. After designing the interactive education system (chatbot) using the feed-forward neural network, this research configured a student sentiment analysis model using the chatbot input. The following briefs the basic structure of the classification model.

### 3.2. Response Classification Model

The proposed research model includes the cloud storage accessibility for the student performance evaluation by analysing the student text input through interactive education application (chatbots). The central application layer, which is at the heart of the whole framework platform, is crucial in developing a cloud computing network teaching platform. This cloud service encompasses all aspects of educational administration, including strategy, management, execution, and assessment. It has enhanced the framework setting of the core application layer by adding network laboratories, teaching tools, search engine, and other functions on an established basis. Users can develop the database, program library, and other features of the application layer framework on a regular basis. Due to the extreme vast volume of data that can be analysed, and perhaps even the identifying information that can be incorporated into the study, big data analysis is critical in this process. This accomplishes the aim of analysing data from various repositories. The students' responses as a result of their tasks, and their interaction with chatbots/IESs, is kept in a structured database. In this research, the chatbot data has been stored and retrieved at the computation unit. In the computation unit, the answers/responses from the students participating in the quiz conducted through the proposed chatbot have been collected through bigdata analysis tools like Hadoop. Then, the collected data has been passed to the deep learning-based text classification model to classify the student responses labelled as Positive, Negative and Neutral.

The response classification model in the computation unit in the proposed AI-IES model uses the Long Short-Term Memory (LSTM) with the attention layer model for the classification [31]. This LSTM model takes the pre-processed data sequences from the student feedback data. The data preprocessing uses the TF-IDF approach and uses the Doc2Vec tokenization, as discussed in the preceding sections. The bag of words is the input that passes to the respective neurons in the LSTM model.

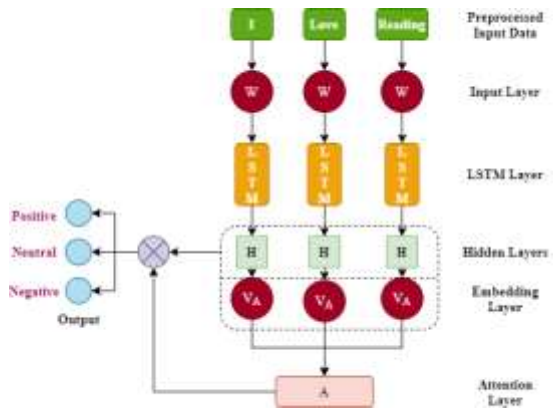


**Figure 5: LSTM Model with Attention Layer for Response Classification**

The general architecture of the proposed response classifier is shown in figure 5, where the embedding layer decides the attention weights combined with the sentence representation for the given bag of words. In general, instead of the word vector {'*I*', '*Love*','*Reading*'}, generic word vector $\{W_1,W_2,W_3,\ldots,W_M\}$ for all $M$ words can be inputted through the input layer. This layer has the same number of neurons respective to input words. The parameter $A$ be the attention weight. The embedded vectors can be thus represented as $\{V_{A1}, V_{A2},\ldots,V_{AM}\}$. The hidden vectors in the hidden layer, in general, can be denoted as a set $\{H_1,H_2,H_3,\ldots,H_M\}$. This classifier can thus classify the student responses as per the executed training. Thereby, the entire AI-IES model can be implemented. The following gives the simulation analysis evaluation and results.

## 4. RESULTS AND DISCUSSION

The research process began with the detailed evaluation of the existing interactive education systems and the use of AI technologies in the education industry along with these interactive systems, as discussed in section 2. Following this, the research hypothesis was formulated to design the intelligent interactive education system (chatbot) explained in section 3. This section includes the evaluation of the proposed chatbot efficiency for both the phases of the designed chatbot and the response classification model.

### 4.1. Chatbot Evaluation Results

The chatbot responses provided by a device or a system are heavily used in content evaluation. Individual evaluation is the most reliable and costly in the field of machine interpretation and text summarization, where machines produce natural-language sentences. Researchers in natural language processing and generation benefit from automated assessment because it helps them perform assessments easily and without the time-consuming manual effort of human judges. One way to measure chatbot efficiency in terms of reaction is to look at accuracy and recall. The evaluation results of both the phases have been included, as follows.

**Phase 1:**

This section evaluates the query and response module based on the similarity scoring function using feed forward neural network. Under this network, the score generation algorithms of BM25 and Doc2Vec representations were individually analysed and the integrated approach of BM25+Doc2Vec representation performance was determined.

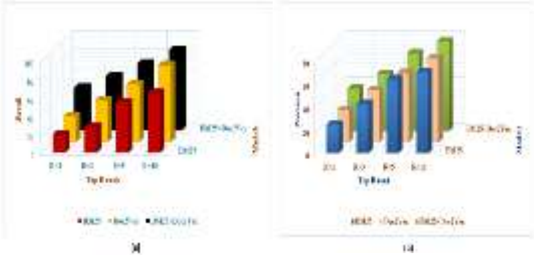

**Figure 2: Chatbot Phase 1 Evaluation Results (a) Recall and (b) Precision**

Figure 2a illustrates the recall value of the text summarization in phase 1, and figure 2b results in the precision measures. Precision and recall are two methods for efficiently evaluating text summarization, which include using a mathematical approach to classify data and context that is important to the interaction. Precision value was identified as the percentage of time that knowledge provided to a conversation is applicable to the subject of the conversation.

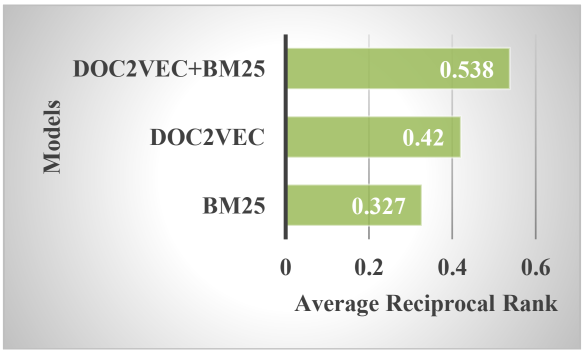


**Figure 3: Average Reciprocal Rank**

Figure 3 demonstrates the average reciprocal rank that determines the mean value of the rank generated for chatbot-generated responses and the student responses. The reciprocal of the rank for all correct responses are first computed and then mean value for these ranks were observed. Based on these results, figure 7 was plotted for all the models used for the scoring and text summarization. The evaluation results were observed with the highest performance for the integrated approach of Doc2Vec + BM25 compared to individual score function and ranking.

**Phase 2:**

In this phase, the questionnaire formation module of the chatbot implementation was assessed. The evaluation parameters used for this phase are answerability and the suitability. The answerability and suitability of the queries/questions for four separate subjects were tested during this process of the assessment. Many approaches use the raw sentences from the document as input; however, this proposed approach used a context-aware, pre-processed version of the document and as said earlier the series of ranking functions has been used to choose the top raw sentences for use as input in the questionnaire formulation module.

**Table 1: Phase Evaluation Results**

| Subject | Suitability | Answerability |
|---|---|---|
| Science | 3.3 | 3 |
| Social | 3.42 | 3.6 |
| Mathematics | 4.8 | 3.4 |
| Politics | 3.9 | 3.22 |
| Business | 4.12 | 3.8 |

A metric on how good the query has been in respect of the evidence it contains and the knowledge that should be required to answer it. In contrast, the sentence suitability can be considered as a possible source text for a quiz question to help in academic education. Such performance metrics were determined by granting access to a panel of 24 independent subject experts to grade/rate the question-answer pairs developed by the questionnaire formulation module. The degrees of answerability of a question were considered by various categories for efficient distinguishing. Table 1 showed that implementing context awareness of the entire sentences and filtering out insignificant sentences or queries from the given or generated content improved the average answerability of created questions. It was further shown that the process of scoring sentences improves the text's overall suitability for a questionnaire or quiz.

The proposed chatbot thus accept the input as an uploaded document and thereby allow the students to ask queries related to the respective document or subject or submit quizzes to test their expertise. The evaluation result shown that the query and response module's efficiency was improved by weighting both the semantic properties and the word significance of the phrase to the question asked, using BM25 and feed-forward neural network scores. As a result, the chatbot became capable of handling both precision and recall queries. In addition, the performance of the questionnaire development module was improved by finding sentences may lead to successful quiz questions. With the exclusion of non-declarative sentences, imposing the most context sensitivity sentences within the document's content, and ranking sentences using a series of rating mechanisms, which resulted in a collection of question-answer pairs that were strongly applicable to the subject matter, this significant was obtained.

### 4.2. Response Classification Model Evaluation Results

The classification accuracy of the proposed LSTM model was evaluated by simulating the text classification. The proposed response classification model was trained using the GitHub dataset [32] containing the questions and answers. This dataset was divided into training and testing datasets in the ratio of 50:50, 60:40, 70:30, and 80:20. The following gives the classification results (Positive, Neutral, and Negative) obtained from the simulation.

## 5. CONCLUSION AND THE FUTURE SCOPE

Artificial Intelligence based Interactive Educational System (AI-IES) was suggested in this paper to improve students' interactive sessions in higher education. The AI implementations guaranteed significant changes in the efficiency of teaching and learning. The detailed analysis showed that the IES model could assist teachers in specifically tailoring instruction to their needs and incorporating different aspects of human social interaction and information and communication technology. IES undertook a systematic assessment to define and clarify the role of immersive education in schooling, and to compare the different trends in a global analysis focused on AI strategies in the education sector. When opposed to other tactics, the experimental findings show that AI-IES has the best response rate. In the future, this study planned to extend the response classification model with integrated approach of LSTM and Convolutional Neural Network (LSTM-CNN) model.

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