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RESEARCH ARTICLE

Higher Educational Institution (HEI) Promotional Management Support System Through Sentiment Analysis for Student Intake Improvement

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ABSTRACT Promotional activities with Emotional Intelligence (EI) are more effective than factual information. It is significant in Higher Educational Institutions (HEIs) marketing and reputation management. Choosing an HEI is a crucial decision. Factual information ignites the human brain's analytical characteristics, making logical decisions while choosing an HEI. Promotional activities that target the emotional states push the target group to overlook logic and make emotional decisions. This paper presents a novel HEI Promotional Management Support (PMS) system that utilizes this phenomenon through sentiment analysis to enhance marketing capabilities. A Bi-Directional-Long-Short-Term-Memory (BiLSTM) network has been designed and implemented in this paper to classify the existing students' sentiments into four classes. It classifies the sentiment with an average accuracy of 92.75%. The positive sentiment of the students is used to target the promotional content, whereas negative sentiment guides to avoid content that has the probability of raising negative concerns. The application of this novel PMS system demonstrates a 4.78% improvement in student intake over an observational period of 24 months. The unique concept, effective implementation, and remarkable result indicate that the proposed HEI Promotional Management Support System is a revolutionary application of Artificial Intelligence (AI) to improve student intake rate.

INDEX TERMS Sentiment analysis, promotion management system, higher educational institutions (HEIs), student intake improvement, BiLSTM, marketing capability, reputation management.

I. INTRODUCTION

Emotion is a natural human characteristic [1]. It pushes a human mind to make decisions overlooking logical analysis [2]. That is why promotional activities targeting sentimental issues have a more profound impact than informative promotion. This effect can be either positive or negative. The positive effect increases the probability of the promotional campaign's success. On the other hand, a negative effect potentially leads to devastating results [3]. This paper presents a novel concept of Higher Educational Institution (HEI) promotional strategies through sentiment analysis. This method identifies and uses the factors related to positive sentimental experiences as promotional content. To our best knowledge, according to the literature review presented in section II, this is the first attempt to incorporate Artificial Intelligence (AI) to discover effective promotional content through sentiment analysis of the stakeholders for HEIs.

AI has revolutionized numerous sectors, including Healthcare [4], Robotics [5], Autonomous vehicle [6], Microbiology [7], Agriculture [8], Education [9], Pharmaceuticals [10], Cyber Security [11], and Human Resource Management [12]. The successful diversified application of AI has motivated the methodology of this paper [13], [14]. However, its application is HEI promotional management system is still unexplored. This paper uses a Bi-Directional-Long-Short-Term-Memory (BiLSTM) network to classify the sentiment from the feedback of stakeholders of HEIs. The sentiment

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classifier classifies the sentiment into four classes. These classes are Average, Good, Neutral, and Poor. This classification is used to identify the positive and negative sentiments of the stakeholders about different offices and sections of HEIs. This classification is used in promotional activities through an innovative Promotional Management Support (PMS) system.

The development of the proposed PMS system and its experimental analysis are the core novelty of this paper. This innovative application of Natural Language Processing (NLP) promotes HEIs by influencing positive emotional impact in potential students worth attention because of the following contributions:

- **PMS Development:** This is the first research that focuses on developing PMS for HEIs that incorporates NLP through the BiLSTM network,
- **Intake Rate Improvement:** The practical application of the PMS system increases the student intake in HEIs by 4.78%, another contribution of this research.
- **Analytic Strategies:** As this is the first-ever research conducted in this field, the performance analytic strategy development is another significant contribution of this experiment.
- **Systematic Performance Analysis:** This paper lays the foundation of conducting a systematic performance analysis of the novel NLP-based PMS system for HIEs

In a nutshell, this paper presents a revolutionary marketing strategy for a higher educational institution to leave a long-term positive impression among future potential students and improve the student intake rate.

The remainder of this paper is systematically structured into seven distinct sections. The second section provides an exhaustive review of the pertinent literature. This section also identifies and articulates the gaps in existing research and the specific objectives of the present study. The third section is devoted to detailing the research methodology employed. The fourth section discusses the experimental results obtained from the proposed methodology, thoroughly evaluating these findings. The real-world application of the system is presented in the fifth section. The sixth section delves into the limitations of the proposed PMS system while also discussing potential avenues for future research and development. Finally, the seventh section provides a comprehensive conclusion to the paper.

II. LITERATURE REVIEW

Kanwar and Sanjeeva [15] created a novel method to assess student satisfaction in different educational sectors in India. The survey method's ability to gauge overall satisfaction and address crucial higher education concerns was highlighted. It demonstrates the linkage between student satisfaction and admission rate in educational institutions. However, this study does not derive any strategy to use the findings to improve the student intake rate, which has been done in the proposed paper. Tran et al. [16] surveyed 25,631 students in 11 provinces in Vietnam and found widespread satisfaction criteria with education services. Educational activities, environment, and access influenced the study. The report did not offer solutions to improve student intake and retention, as our paper proposed. Finally, Darawong and Widayati [17] examined how four factors-reliability, responsiveness, competence, and empathy-affect student satisfaction in Indonesian and Thai bachelor's degree programs. Thai students valued reliability, whereas Indonesians valued empathy. These studies illuminate Asia's higher education student satisfaction factors. Identifying these factors and resolving gaps might improve educational opportunities by attracting and intaking in more students at these schools. The hypothesis of our paper has been developed from the observation in these literature reviews to overcome the weaknesses found in these literature reviews.

The studies by Nuseir and El Refae [18], Rosyidah et al. [19], and Milian [20] highlight the importance of promotional strategies in university selection and internationalization. However, there is a research gap in the implementation of the findings. The proposed paper applies AI to automate the promotional decision-making process. M. T. Nuseir et al. [18] found five factors influencing students' choices in UAE universities, while Rosyidah et al. [19] explored promotion tactics for building global trust and increasing student enrollment. R.P. Milian's [20] study examined Canadian universities' promotional approaches amidst increased competition for funding. All three studies emphasize the need for a strong vision, international accreditation, effective communication, and fostering collaborations. Scholarships for foreign students and promoting inclusivity can also boost universities' appeal. These observations indicate that multiple measurable factors influence the student intake rate. These factors are closely connected with the emotional states of the students, which has been used the proposed methodology. Understanding these factors help universities worldwide adapt to the rising competition and develop effective strategies for attracting students. The methodology of the proposed paper has been developed based on this conclusion. However, the BiLSTM network-based automation has added a remarkable novelty to the proposed paper.

Tan et al. [21] presented EVA, a novel SA feature for identifying text emotional instability. This work has the potential to be applied in the fields of mental health as well as consumer behavior. The potential students who may be interested in taking admission are considered consumers in this paper. The proposed HEI PMS system has adapted the concept of considering students as consumers. Sentiment analysis, deep learning, and dictionary-based approaches were used by Ren et al. [22] to examine free-form student input to evaluate the instructors' performance. The results revealed insights that were captured by qualitative data. It lays out some of the strategies used in the paper, which have been modified to quantitative data. Amraouy et al. [23] emphasized the importance of machine learning and lexicon-based assessments for evaluating socio-affective abilities in education systems. This provides a comprehensive approach to measuring learning outcomes considering cognitive and socio-affective capabilities. It supports the methodology of the proposed paper, which is based on a BiLSTM network-based sentiment classifier.

A. RESEARCH AREA & OBJECTIVE ANALYSIS

One of this paper's research areas and objectives is to apply Emotional Intelligence (EI) in HEI's promotional activities. Kidwell et al. [24] prove that applying EI is practical in bringing favorable outcomes in sales and marketing. The findings of this paper has motivated the proposed HEI PMS system. The study of N. Nwokah et al. concludes that EI is effective in marketing [25]. Similar findings have been presented in the study of Prentice [26]. J. Hutchins et al. applied emotional intelligence in branding, exhibiting remarkable improvement in marketing and branding. These studies direct that EI is effective and valuable in the marketing and branding of various industries. According to the Service Marketing Theory (SMT), the fundamental marketing concept is the same for all sectors [27]. This analysis concludes that EI also plays a significant role in HEI marketing.

The proposed Higher Educational Institution (HEI) promotional management support system through sentiment analysis for student intake improvement combines three research fields in table 1. The related research and the objectives of those research are also summarized in the same table. Student satisfaction directly relates to Higher Educational Institutions (HEIs) promotional activities. Multiple factors govern student satisfaction [28]. However, these factors vary from different perspectives. Factors influencing student satisfaction in HEIs are a vibrant field of research [29]. Student satisfaction has a direct impact on the marketing strategy development of HEIs [30]. And sentiment analysis is an intuitive and human-like approach to analyzing students' sentiments [31]. The combination of these different but interrelated research fields facilitates the scope of development of the proposed promotional management system.

B. IDENTIFYING RESEARCH GAP

A Promotional Management Support (PMS) system for Higher Educational Institutions (HEI) through sentiment analysis to improve student intake requires combining research related to student satisfaction factors, marketing strategies, and sentiment analysis. While these areas are a well-developed research field, there are some limitations in the context of the proposed PMS system. From the literature review, it has been observed that there are numerous limitations in the current phase of research in HEI promotional activities. Manual analysis of the survey response, question and answer-based approach without considering the emotion, analysis on a limited number of factors, human biases in evaluation, similarity measure-based approach, sentiment analysis-based approach without exploring application domain, and lack of proper feedback evaluation is the most significant research gaps. This paper fills up this gap by the innovative HEI PMS system.

TABLE 1. Summary of the literature review, closely relevant to the proposed system.

Review Area	Authors	Objectives
Student satisfaction factors	A. Kanwar et al. [15]	Discovering the development and implementation of a Student Satisfaction Survey for higher education institutions in India
	H.H. Tran et al. [16]	Identifying student satisfaction level based on the quality of educational environment in Vietnam
	C. Darawong et al. [17]	Analyzing the Thai and Indonesian students on four service quality parameters on student satisfaction
Marketing Strategy	M.T. Nuseir et al. [18]	Factors that influence effective marketing strategies of universities
	N. Rosyidah et al. [19]	Exploring the effective promotional strategies for build global brand to increase student enrollment
	R. P. Milian [20]	Discovering promotional tactics to increase financial influx
Sentiment Analysis	L. Tan et al. [21]	Emotional Variance Analysis (EVA)-based profiling to predict academic performance
	P. Ren et al. [22]	Automatically measure the emotional state of the students based on their textual feedback
	M. Amraouy et al. [23]	Assessing the socio-affective abilities in education system using sentiment analysis

Deep Learning (DL)-based sentiment analysis identifies the human sentiment from student feedback [32]. These sentiments are the indicator of the student's satisfaction level [33]. The students' satisfaction levels are also governed by factors that are the pivot points of developing marketing strategies. What satisfies the students should be highlighted, and what causes negative impact should be ignored and mitigated [34]. However, the literature review shows that no research has explored combining these three sectors and developing an intelligent PMS system to increase the rate of student intake in HEIs.

III. METHODOLOGY

The proposed Higher Educational Institution (HEI) promotional management support system, illustrated in figure 1, is an artificial intelligence-powered system that helps HEIs improve the rate of student intake through effective marketing. Usually, HEIs are large-scale organizations with multiple sections [35]. It is beyond any large-scale organization's scope to have the same level of service from different sections. As a result, some departments and sections become more popular than others. Identifying the popular sections and promoting the HEIs by highlighting those sections is more effective than random promotion.

However, identifying the popular sections of the HEIs is challenging. Traditional suggestion box hanging outside

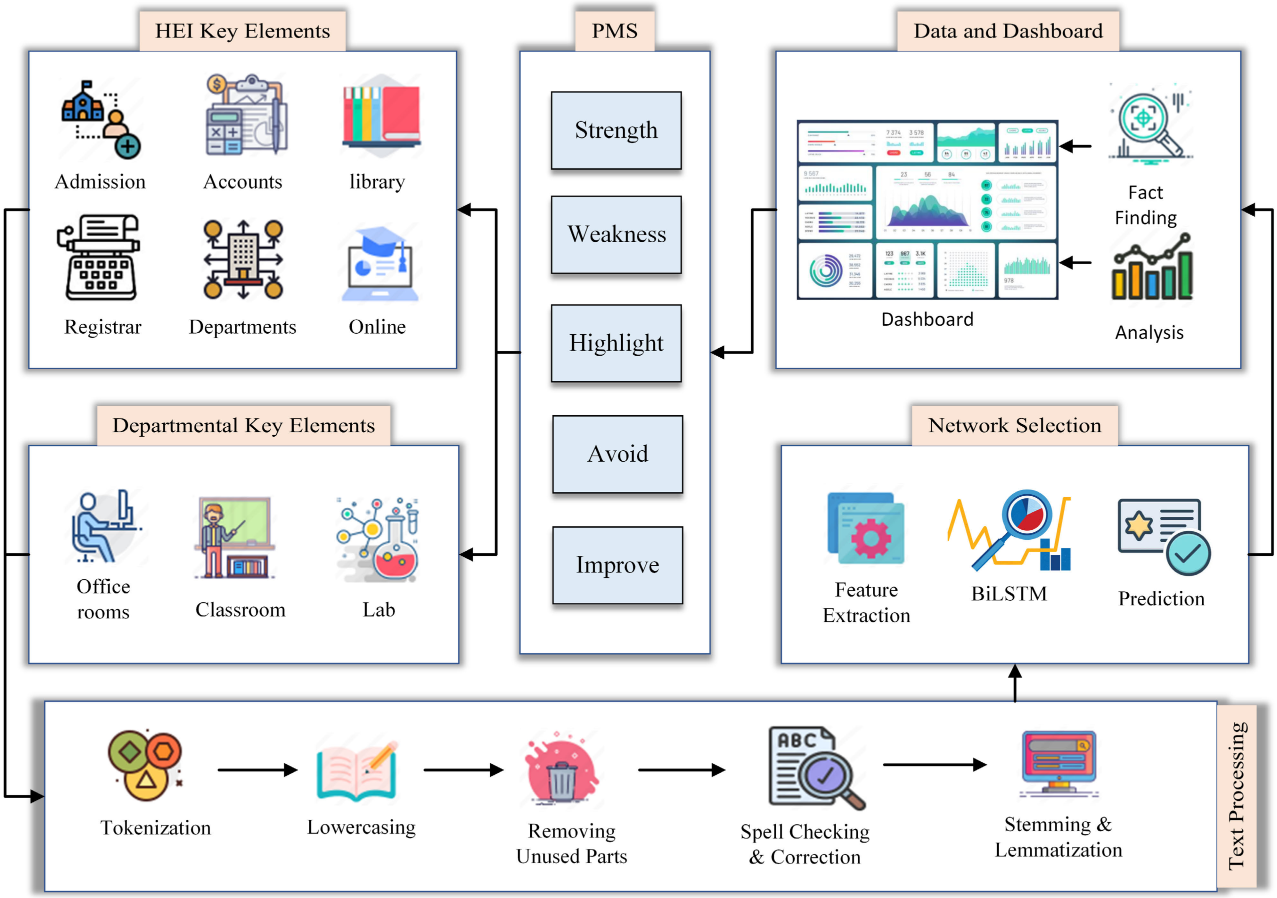

FIGURE 1. **The overview of the proposed methodology.**

different offices and departments is no longer practical. Multiple choice-based forms confide the users within some specific set of choices that do not reflect the sentiment of the students [36]. That is why sentiment analysis is a potentially effective way to discover the popularity of the sections of HEIs. The proposed methodology offers student feedback opportunities after getting services from different sections and departments of HEIs. This feedback contains suggestions, appraisals, complaints, and human sentiment, which is the root cause of the corresponding feedback. These text data are processed by following the state-of-the-art text processing methods of Natural Language Processing (NLP) [37]. The features are extracted from the processed texts that train a Bidirectional Long Short-Term Memory (BiLSTM) network [38]. It predicts the sentiment of the students. This sentiment is analyzed, and according to proper facts and findings, a dashboard shows the status of different departments and sections. The promotional management system finds the strengths, weaknesses, highlights, scope of improvement, and things to avoid while promoting the HEI.

A. DATASET PREPARATION

Dataset preparation plays a crucial role in the performance of Deep Learning models [39]. This paper uses the stakeholders' feedback as the dataset, strings with variable length. The scalable machine learning model is essential to utilize this variable-length dataset [40]. At the same time, there is no control over the stakeholders' feedback. Data sparsity, including single-word feedback, meaningless feedback with symbols, or nominal or no meaning, impose additional challenges [41]. These challenges have been overcome through text processing.

1) DATASET COLLECTION

The data collection is a crucial step of the proposed Promotional Management Support (PMS) system. It is exclusively focused on Higher Educational Institutions (HEIs). The essential elements of an HEI are the admission section, account & finance section, library, registrar's office, and different departments. The departments consist of office rooms, classrooms, and laboratories. Student dissatisfaction with any of these elements harms the overall outlook of an HEI. The dataset collected for this project has been prepared from the students' feedback about these sections of a university. The dataset collection process is defined by equation 1

$$D[S_{array}] = \sum_{i=0,j=0}^{m,n} F[s_{ij}] \tag{1}$$

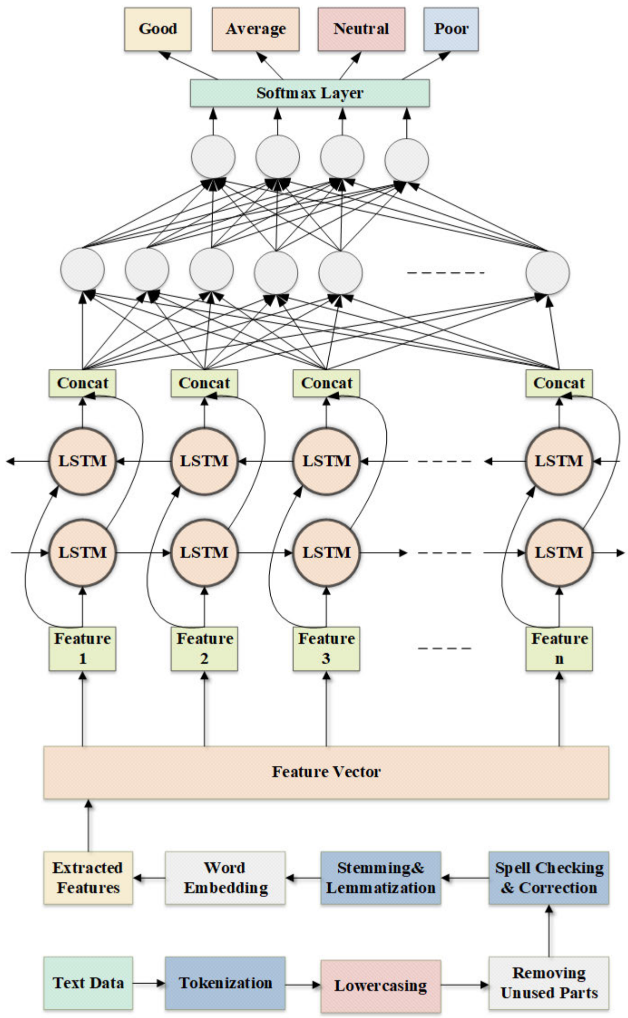

FIGURE 2. The technical methodology.

Here, $D[S_{array}]$ is the memory location for the dataset where the feedback is stored in S_{array}, which is an array. The i and j are indices of different offices and individuals, respectively. The m and n are the maximum number of offices and responses. The $F[s_{ij}]$ represents the feedback of the j^th stakeholder about i^th office. Once the dataset is collected, it is labeled by human inspection according to equation 2 where $H()$ is a function that represents the human inspection.

$$\{F, L\} = \{S_{array}, H(S_{array})\} \tag{2}$$

After labeling, each instance on the dataset becomes a 'feedback, label' pair. These instances are used to train the proposed PMS system. The data source for this experiment is the stakeholders' feedback. These data are collected through feedback digital feedback forms. After getting some service from any section of an HEI, the stakeholders get the scope to provide their feedback on the feedback form. This feedback is the source of the data.

2) TEXT PROCESSING

The dataset contains text data explaining the opinion of the students about different sections of a university. These text data represent the sentiment of the student. The dataset inspection shows many spelling mistakes and improper words in the feedback. The punctuation, numbering, and capital letters have no direct connection with the sentiment the text data carry. It is essential to process the text data before extracting features from them. This section explains the text processing methodology used in this paper, illustrated in figure 2.

a: TOKENIZATION

The first step of text processing used in this research is tokenization. The feedback of the students has been broken into small pieces called tokens through this process which is defined by equation 3 where $f(w_i)$ represents the function applied to each token w_i in the text.

$$f(w_i) = w_i \; \forall \; w_i \in T \tag{3}$$

In the equation, 3, for each token w_i in the text, the function returns the same token w_i. It removes the repetitive tokens from the feedback expressed as T.

b: LOWERCASING

The uppercase or lowercase letters have no direct impact on the sentiment of the students' feedback. It is common to convert texts into lowercase to avoid unnecessary complexities. It helps to reduce vocabulary size and improve the performance of various natural language processing tasks. The lowercasing method of this research is defined by equation 4

$$f(c_i) = \begin{cases} \text{lower}(c_i), & \text{if } c_i \in A \\ c_i, & \text{otherwise} \end{cases} \tag{4}$$

In equation 4, the $f(c_i)$ represents the function applied to each character c_i in the students' feedback dataset. If the character c_i is in the set of allowed characters A, the function returns the lowercase form of the character using the function lower(c_i). As a result, any capital letter turns into a lowercase letter. However, the function returns the same character c_i for any other case.

c: REMOVING PUNCTUATION

Removing punctuation is another essential step for Natural Language Processing (NLP). It has been done in this research to improve the performance of the proposed sentiment analyzer. The mathematical definition expressed in equation 5 is used to remove punctuation in this paper.

$$f(c_i) = \begin{cases} c_i, & \text{if } c_i \notin P \\ \text{remove}, & \text{otherwise} \end{cases} \tag{5}$$

Here, $f(c_i)$ represents the filtering function applied to each character c_i in the text. If the character c_i is not a punctuation mark, the function returns the same character c_i. Otherwise, the character c_i is marked for removal. To remove punctuation marks from a text, the filtering function $f(c_i)$ has been applied to all characters in the text, and then remove the characters marked for removal.

d: REMOVING STOP WORDS

Stop words are frequently used terms in a language that do not add much to the meaning of the text or the NLP process as a whole. One common preprocessing step to boost the efficiency of NLP applications is the removal of stop words. That is why we removed them using equation 6

$$f(w_i) = \begin{cases} w_i, & \text{if } w_i \notin S \\ \text{remove}, & \text{otherwise} \end{cases} \tag{6}$$

In this equation, $f(w_i)$ represents the filtering function applied to each word w_i in the text. If the word w_i is not a stop word, the function returns the same word w_i. Otherwise, the word w_i is marked for removal. To remove stop words from a text, you would apply the filtering function $f(w_i)$ to all words in the text and then remove the words marked for removal. This equation provides a simple and effective method for removing stop words from a text, which can improve the performance of the proposed sentiment analyzer.

e: REMOVING SPECIAL CHARACTERS & NUMBERS

A similar approach to removing stop words have been used to remove special characters and numbers from the dataset. It is a common preprocessing step in NLP. In this research, it has been done using equation 7 where $f(c_i)$ represents the filtering function applied to each character c_i in the text.

$$f(c_i) = \begin{cases} c_i, & \text{if } c_i \in A \text{ remove}, & \text{otherwise} \end{cases} \tag{7}$$

f: SPELL CHECKING & CORRECTION

Spell checking and correction in natural language processing typically involves finding the most likely correct word for a given misspelled word. One common approach is based on the noisy channel model, which involves finding the correct word c that maximizes the probability $P(c|w)$, where w is the misspelled word. It is defined using Bayes's theorem as equation 8

$$\hat{c} = \arg\max_{c \in C} P(c|w) = \arg\max_{c \in C} \frac{P(w|c)P(c)}{P(w)} \tag{8}$$

In equation 8, C is the set of candidate words, $P(c|w)$ is the posterior probability of the correct word given the misspelled word, $P(w|c)$ is the likelihood of the misspelled word given the correct word, $P(c)$ is the prior probability of the correct word, and $P(w)$ is the probability of the misspelled word.

g: STEMMING & LEMMATIZATION

Stemming is a heuristic text normalization process that removes affixes (suffixes and prefixes) from words in natural language processing. It can be represented using a function $s : W \rightarrow W'$, where W is the set of all words in a given text, and W' is the set of stemmed words. For a word $w \in W$, the stemming function $s(w)$ is expressed as equation 9 where stem(w) represents the stem of the word w. The stemming function is applied to all words in the text to obtain a new set of words W'.

$$s(w) = \text{stem}(w) \tag{9}$$

Because it is a heuristic, stemming may not always give you the best representation of a word's root. Sometimes inaccurate answers are produced because stemming ignores the context and the part of speech of the word. That is why lemmatization is performed as well. It is a more sophisticated approach to text normalization that reduces words to their base or dictionary form, called a lemma. It involves morphological analysis and considers the context and part of speech of the word in the text. The lemmatization process used in this research is expressed in equation 10. Here $l : W \rightarrow W'$ is a function where W is the set of all words in a given text, and W' is the set of lemmatized words.

$$l(w) = \text{lemma}(w, \text{POS}(w)) \tag{10}$$

Here, lemma(w, POS(w)) represents the lemma of the word w with its corresponding part of speech, denoted by POS(w). The lemmatization function is applied to all words in the text to obtain a new set of words W'.

h: REMOVING OR REPLACING SPECIFIC WORDS

The dataset inspection shows words that are not defined in any dictionary of the experimenting language. These types of words affect the overall performance of the sentiment analyzer. The process of removing or replacing specific words in natural language processing has been represented using a function that maps the original sequence of words to a new sequence with some words removed or replaced according to a given criterion where the sequence of words, $S = \{w_1, w_2, \ldots, w_n\}$ and w_i is the i-th word in the sequence. The mathematical expression of this process is defined by 11.

The process of removing or replacing specific words can be defined as:

$$f(w_i) = \begin{cases} w_i, & \text{if } w_i \notin R \\ g(w_i), & \text{if } w_i \in R \end{cases} \tag{11}$$

The function, $f : S \rightarrow S'$, maps the original sequence S to a new sequence S', with some words removed or replaced according to a given criterion. Let R be the set of words to be removed or replaced, and let $g : R \rightarrow R'$ be a function that defines how words in R should be replaced.

B. FEATURE EXTRACTION

The literature review shows three different frequently used ways to extract features from the processed text data for sentiment analysis. They are Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and Word Embeddings. This research experimented with all three of these feature extraction methods. The BoW method, defined in equation 12 represents each document as a vector of word frequencies. A dimension in the vector represents each word in the vocabulary, and the value in each dimension represents the frequency of that word in the document.

$$x_{i,j} = \mathrm{freq}(w_j, d_i) \tag{12}$$

In equation 12, the $x_{i,j}$ is the frequency of word j in document i, and $\mathrm{freq}(w_j, d_i)$ is the frequency of word j in document i.

Term Frequency-Inverse Document Frequency (TF-IDF) is another popular and frequently used method which is defined by equation 13 where $x_{i,j}$ is the TF-IDF weight of word j in a document i, $\mathrm{tf}(w_j, d_i)$ is the term frequency of word j in document i, and $\mathrm{idf}(w_j)$ is the inverse document frequency of word j. It represents each document as a vector of term frequencies weighted by their inverse document frequency. The inverse document frequency weight reflects the importance of a term in a document collection.

$$x_{i,j} = \mathrm{tf}(w_j, d_i) \times \mathrm{idf}(w_j) \tag{13}$$

The Word Embeddings (WE), defined by equation 14, where $x_{i,j}$ is the embedding vector of word j in document i, and $\mathrm{emb}(w_j)$ is the embedding vector of word j, represents each word in the vocabulary as a dense vector of fixed size. Word embeddings capture the semantic and syntactic relationships between words and are trained on large corpora of text data.

$$x_{i,j} = \mathrm{emb}(w_j) \tag{14}$$

All three of these methods have been explored in this research project, and the Word Embedding (WE) has been selected for better performance.

C. NETWORK SELECTION AND ARCHITECTURE

1) NETWORK SELECTION

The core part of the proposed PMS system is a sentiment analyzer where the BiLSTM network has been used. Variable-length datasets consisting of strings have been used in this paper. The dataset's string, or set of text, expresses the users' sentiment. The lengths of the texts depend on the users' emotional states. Moreover, limiting the length leads to the potential loss of some users' sentiments. As a result, it is beyond the scope to use fixed-length data. The Long Short-Term Memory (LSTM) network is standard to work with variable length input [42]. It is designed to learn from sequential data [43]. The dataset used in this experiment contains variable lengths of sequential data. That is why the LSTM network is a suitable network for it. However, it uses a single-directional cell. Both current, previous, and future sequences are adequate in sentiment analysis. A Bidirectional Long Short-Term Memory (BiLSTM) network has the capability to explore both backward and forward states with respect to the current state [44]. That is why the BiLSTM network has been used in this paper.

2) NETWORK ARCHITECTURE

In this experiment, the BiLSTM network, illustrated in figure 2, has been used to analyze the sentiment of the students. It is a type of Recurrent Neural Network (RNN) architecture that is capable of processing sequential data in both forward and backward directions. The BiLSTM has been used in this research for its capability to capture both past and future sequence context [45]. As a result, the sentiment analyzer can analyze and recognize human sentiment with better performance.

The input, forget, and output gates are defined by equations 15, 16, and 17 where x_t is the input at time step t and h_t is the hidden state of the network at time step t.

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{15}$$
$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \tag{16}$$
$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \tag{17}$$

The candidate cell state, an essential element of the BiLSTM network, is calculated by equation 18. The cell state is defined by equation 19. Here, W and b are the weight matrix and bias vector, respectively.

$$\tilde{c}t = \tanh(Wxcx_t + W_{hc}h_{t-1} + b_c) \tag{18}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{19}$$

The cell output is calculated by equation 20 where σ and $\odot$ are the sigmoid and element-wise multiplication operations, respectively.

$$h_t = o_t \odot \tanh(c_t) \tag{20}$$

The BiLSTM network has two LSTMs: a forward LSTM and a backward LSTM. The forward LSTM processes the input sequence in the forward direction, while the backward LSTM processes the input sequence in the reverse direction. The backward LSTM computes the same equations as the forward LSTM, but with the input sequence in the reverse direction. The final output of the BiLSTM network is obtained from equation 21 where $h_t^{(f)}$ and $h_t^{(b)}$ are the outputs of the forward and backward LSTMs at time step t, respectively.

$$y_t = [h_t^{(f)}, h_t^{(b)}] \tag{21}$$

3) LEARNING ALGORITHM

The Adaptive Moment Estimation (ADAM) optimization algorithm has been used in this experiment as the learning algorithm of the proposed network [46]. The ADAM algorithm updates the weights using equations 22 and 23 where w is the network weights, g is the gradients of the loss function concerning the weights, and θ is the parameters of the ADAM optimizer. The equation 22 is used to calculate the moments, and the equation 23 is used to calculate the gradients.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)g_t \tag{22}$$
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)g_t^2 \tag{23}$$

In equations 22 and 23, m_t and v_t are the first and second moments of the gradients at time step t, β_1 and β_2 are the decay rates for the first and second moments, respectively. Correcting the bias of the first and second moment estimations is essential, which are done by equations 24 and 25, respectively.

Compute bias-corrected first and second-moment estimates:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \tag{24}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \tag{25}$$

Finally, the weights are updated using equation 26 where α is the learning rate, ϵ is a small constant added for numerical stability.

$$w_{t+1} = w_t - \frac{\alpha}{\sqrt{\hat{v}_t}+\epsilon}\hat{m}_t \tag{26}$$

IV. EXPERIMENTAL RESULTS & EVALUATION

The proposed PMS system contributes to the overall marketing strategy of the HEIs by ranking different key elements of an HEI into five categories. These categories are - Strengths, Weaknesses, Highlight, Avoid, and Improve. The marketing strategies are developed using the strength of an HEI, which is good enough to highlight. As the system is developed using the feedback of the stakeholders, which is deliberately provided, there is no ethical concern towards the system. The sentiment analysis-based classification is at the heart of the HEI Promotional Management Support System. The entire support system depends on the prediction of the BiLSTM network. It classifies the sentiment of the stakeholders into four classes: Good, Average, Neural, and Poor. The promotional activities are conducted based on this classification. That is why the core focus of the experimental results and evaluation is on classification accuracy. This section presents the experimental results and evaluates those results to identify the effectiveness of the proposed system in accurately classifying sentiments.

A. EVALUATION METRICS

The state-of-the-art classification algorithm evaluation metrics have been used in this research. It has been observed that accuracy, precision, recall (sensitivity), specificity, and F1 Score are defined by equations 27, 28, 29, 30, and 31, respectively, are the metrics used to evaluate a classifier's performance. These metrics depend on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which are retrieved from confusion matrix analysis [47].

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \tag{27}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}} \tag{28}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{29}$$

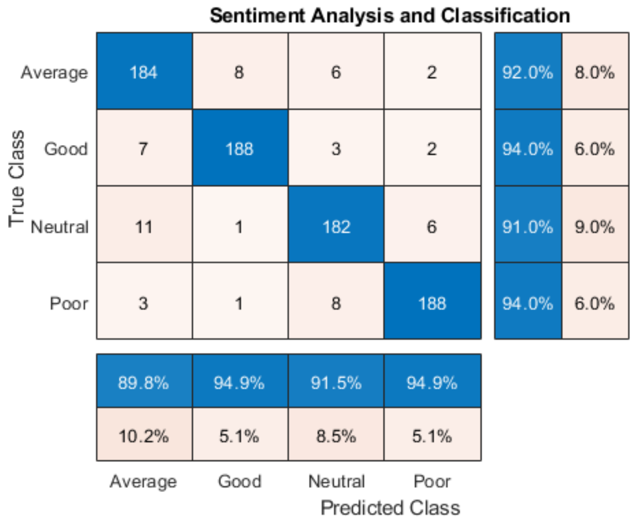

FIGURE 3. Confusion matrix.

TABLE 2. Performance of the classifier based on confusion matrix analysis.

Class	Precision	Recall/Sensitivity	Specificity	F1 Score
Average	0.8976	0.92	0.964	0.9087
Good	0.9495	0.94	0.9822	0.9447
Neural	0.9146	0.91	0.9702	0.9123
Poor	0.9495	0.94	0.9822	0.9447

$$\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}} \tag{30}$$

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision}+\text{Recall}} \tag{31}$$

B. CONFUSION MATRIX ANALYSIS

The confusion matrix, illustrated in figure 3, has been generated from test data. The trained network has been tested with 800 test data that have not been used before. A balanced test dataset has been used where each class has 200 instances. The confusion matrix analysis for the four-class classification problem yielded valuable insights into the model's performance. The model's overall accuracy was 0.9275, indicating that the model correctly predicted 92.75% of the cases.

Upon examining the individual classes, the model displayed a balanced performance across all categories which has been listed in table 2. The Average class had a precision of 0.8976, a recall of 0.92, and an F1 Score of 0.9087, while the Good class achieved a precision of 0.9495, a recall of 0.94, and an F1 Score of 0.9447. The Neutral class registered a precision of 0.9146, a recall of 0.91, and an F1 Score of 0.9123. Finally, the Poor class exhibited a precision of 0.9495, a recall of 0.94, and an F1 Score of 0.9447. These results demonstrate that the model performs relatively well in differentiating between the various classes, as evidenced by the consistently high precision and recall values. The specificity values also indicate that the model effectively identifies true negative cases for each class.

TABLE 3. True Positive Rate (TPR) and False Positive Rate (FPR).

Class	TPR	FPR
Average	0.92	0.036
Good	0.94	0.0178
Neutral	0.91	0.0298
Poor	0.94	0.0178

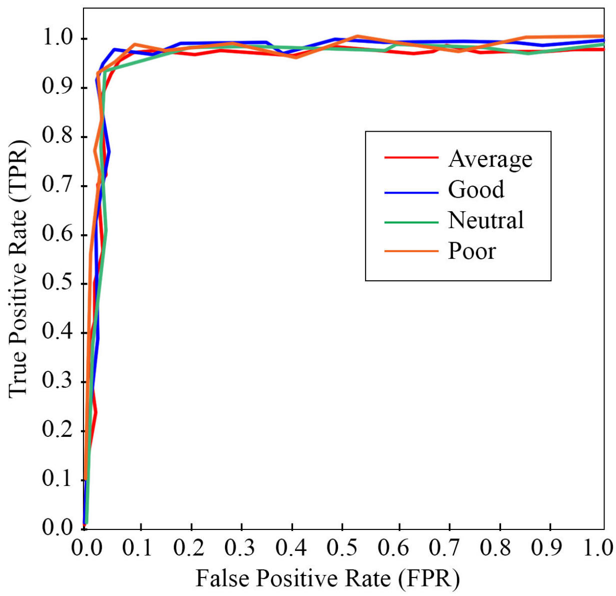

FIGURE 4. AUC-ROC analysis.

According to the data in table 2, the model appears to have a robust performance across all classes, as evidenced by the high accuracy, precision, recall, specificity, and F1 Score values. This suggests that the model is reliable for predicting the categories of Average, Good, Neural, and Poor, with minimal false positives and false negatives. However, there is still room for improvement, particularly in the Average and Neutral classes, where the precision and recall values could be further optimized.

C. AUC-ROC ANALYSIS

The performance of the proposed system has been further analyzed using Area Under the Receiver Operating Characteristics (AUC-ROC). It requires the values of True Positive Rate (TPR), which is the sensitivity or recall, and the values of False Positive Rate (FPR), measured using equation 32. The values of TPR and FPR are listed in table 3.

$$FPR = 1 - specificity \tag{32}$$

The average ROC-AUC for TPR is 92.75%. On the other hand, the average FPR is 7.25%. It indicates that the proposed model accurately classifies positive and negative classes. Figure 4 illustrates the performance of the proposed network for each class in terms of ROC-AUC. It shows an insignificant difference. That means the proposed network maintains persistent performance for each category.

V. IMPLEMENTATION & ANALYSIS

The proposed Higher Educational Institution (HEI) promotional management support system has been implemented using the experimenting institution using a server provided by the institutional data center. The institution has equipped a Virtual Machine (VM) with 16GB of primary memory and four core virtual Processors with a 3.60GHz clock speed. The proposed system consists of three modules. The first module is the sentiment analyzer. The second module is the web server. And the third module is the decision support system. The web server maintains communication with the sentiment analyzer and decision support system. Figure 5 illustrates the implementation procedure of the proposed system.

The core sections of education institutions have their own customized HTML form to collect the stakeholders' feedback. The feedback form is not traditional, with limited options controlling the user's choice. Here, users are free to express their feelings and provide feedback. The database receives the user's feedback using the HEI PMS System database controller. The form creation and transferring the input to the database are the responsibility of the web server. The database server maintains four types of tables. The User Feedback table stores the feedback of the users in plain text. The Structure Meta table defines the structure of the entire database. The Training Data table contains the processed text for training the BiLSTM network. Once the network is trained, it predicts the sentiment related, which is stored in the PMS data table. A decision logic module controls the data stored in the PMS module.

There are two types of users of this system. One is the admin user, and another is the management user. The admin users can access the database, BiLSTM network, and decision logic. They have access to retrain the BiLSTM network using the training data. The admin users have the privilege to remove inappropriate feedback as well. The core focus of this paper is on the management users. The management users select the date range from the user interface. Then the BiLSTM network classifies the responses of the users. Based on the classification, the PMS analytics generate promotional support information. The management users use this information to promote their institution effectively.

The proposed HEI PMS system has been studied through real-world experiments. The data have been collected over six months. During this time, more than 1200 responses have been collected. After cleaning the feedback, 1050 responses were found valid. These valid responses are used to predict to test the proposed BiLSTM network. In this experiment, both human and BiLSTM networks are used. First, the sentiments were classified using human observation. After that, the same data were fed into the BiLSTM network, and the prediction was generated. It has been observed that the human analysis and BiLSTM network's sentiment analysis are almost identical. The data in the table 4 compares sentiment analysis conducted through human inspection and a BiLSTM-based sentiment analyzer. The results are organized by month and

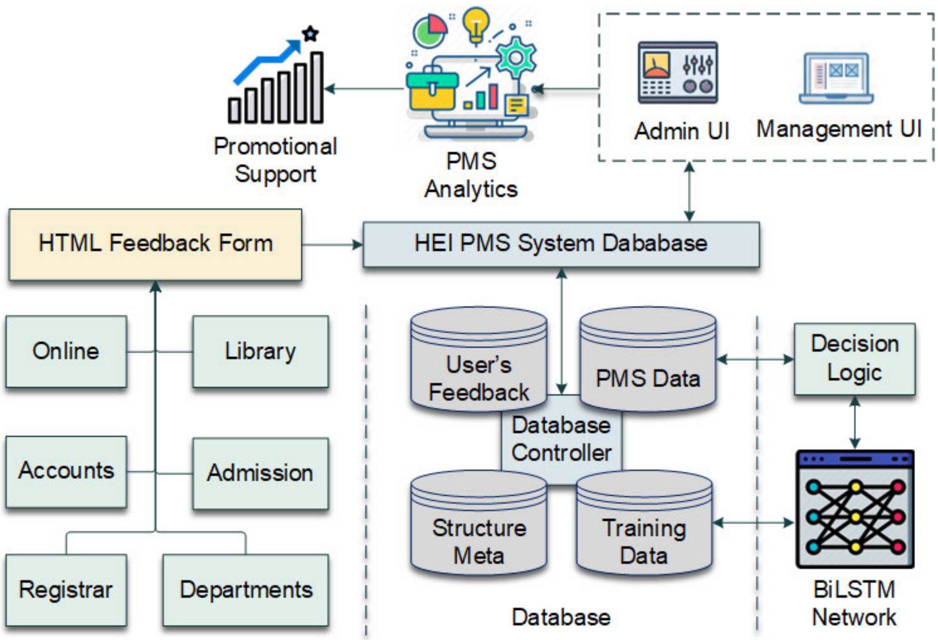

FIGURE 5. The implementation overview of the proposed HEI PMS system.

include four sentiment categories: average, good, neutral, and poor.

Over six months, the human inspection identified 121 average, 129 good, 181 neutral, and 96 poor sentiments, while the BiLSTM-based sentiment analyzer detected 120 average, 127 good, 177 neutral, and 99 poor sentiments. The results show a close correspondence between the two methods, with only minor discrepancies in sentiment distribution. In particular, the human inspection method found slightly more good and neutral sentiments, whereas the BiLSTM-based sentiment analyzer detected a marginally higher number of average and poor sentiments. The comparison suggests that the BiLSTM-based sentiment analyzer performs comparably to human inspection in identifying and categorizing sentiment across various months. The similarity between human inspection and the BiLSTM sentiment analyzer is more vivid in figure 6. Human error and biases influence the insignificant difference in these two observations.

According to the BiLSTM prediction, the stakeholders' experience with the library is the best. And students' experiences with the accounts section are the worst. For experimental purposes, the social media posts were made by highlighting the accounts section of the institution. Within 48 hours of publishing the post, there were two positive comments, nineteen negative comments, and five neutral comments. However, the social media posts related to the library are well accepted. Within 48 hours, there were thirty-two positive, two negative, and four neutral comments. It indicates that the proposed HEI PMS system effectively makes decisions about promoting the institution using a particular section. It also helps the management to understand which section to improve.

A. STUDENT INTAKE IMPROVEMENT

The experimenting institution has multiple marketing policies. There is no feasible way to pause other marketing strategies and solely depend on the HEI PMS system to discover the effect of it on student intake improvement. That is why the effect of the proposed system has been studied along with regular promotional activities. However, the positive sides of the institution, discovered through the sentiment analyzer, are blended with existing marketing strategies whenever possible. Instead of sharing some random images on social media, the sections with good feedback have been highlighted on social media posts. A similar approach has been followed for print media marketing. The institution has an admission consultancy unit. It was recommended to the unit to highlight the positive part of the university, which was discovered through sentiment analysis.

After applying the HEI PMS system with existing marketing strategies for eight semesters, the admission rate was compared with the previous four semesters. Table 5 demonstrates the impact of implementing the novel HEI Promotional Management Support (PMS) System on student intake over 24 months. The number of student intake in a particular department has been observed for 24 months after using the proposed PMS system. Then the values have been compared with the immediate previous 24 months when the PMS was not applied. Evidently, the proposed sentiment analysis-based approach, designed using a BiLSTM network, has led to an improvement in student intake numbers. On average, there is a 4.78% increase in student intake after implementing the HEI PMS System. The most significant improvement was seen in semester 6, with an 11.11% rise in student intake, while semesters 5 and 8 showed no change. The system has shown

TABLE 4. Real-world experimental data of the proposed HEI PMS system.

	Human Inspection				Sentiment Analyzer			
Month	Average	Good	Neutral	Poor	Average	Good	Neutral	Poor
1	10	18	23	19	11	18	23	20
2	16	24	34	13	15	24	31	13
3	25	19	37	11	24	20	35	11
4	21	20	28	15	21	20	29	15
5	23	25	29	20	23	23	29	21
6	26	23	30	18	26	22	30	19
Total	121	129	181	96	120	127	177	99

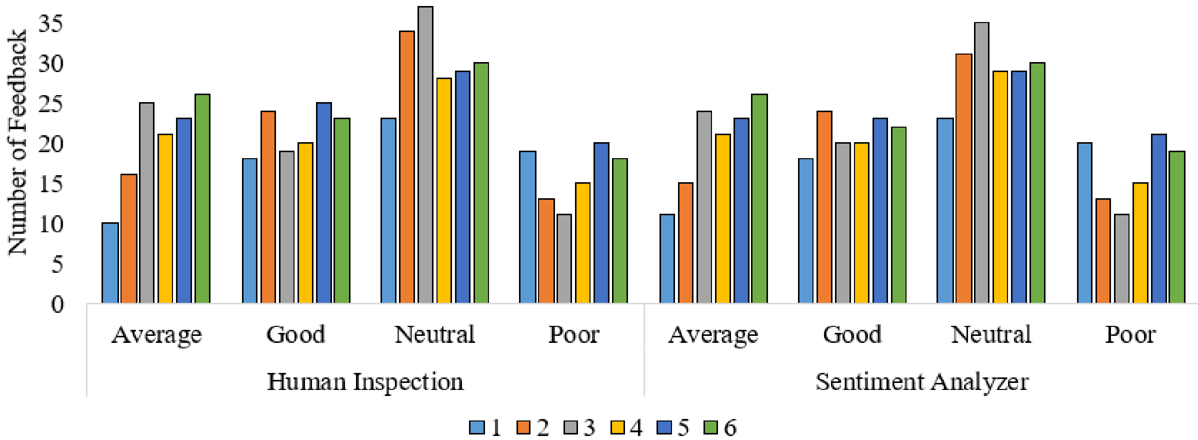

FIGURE 6. Comparison between the BiLSTM prediction and human observation.

TABLE 5. Student intake improvement after using HEI PMS System.

Semester	Before PMS	After PMS	% Improvement
1	44	47	6.38
2	57	62	8.06
3	30	32	6.25
4	54	55	1.82
5	52	52	0.00
6	24	27	11.11
7	62	65	4.62
8	28	28	0.00
Average	44	46	4.78

varying degrees of effectiveness across different semesters, but overall, it has contributed positively to enhancing the student intake for the higher educational institution.

Figure 7 shows that the proposed HEI PMS system improves student intake. However, The admission pattern is almost similar before and after using the system. It indicates the natural pattern which has nothing to do with the proposed system. However, on average, the student intake increases by 4.78%, which is measured by equation 33. The student intake improvement has been presented using a black non-linear curve in figure 7. The student intake improvement analysis shows that the proposed HEI PMS system positively impacts the overall admission rate of higher education intuitions.

$$S_i = \frac{\sum_{i=1}^{m} (PMS_{Ai} - PMS_{Bi})}{\sum_{i=1}^{m} PMS_{Ai}} \times 100\% \tag{33}$$

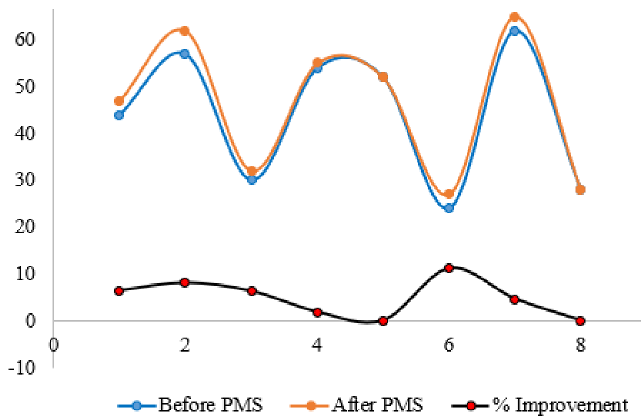

FIGURE 7. The improvement in student intake.

In equation 33, S_i is the student intake increase rate, and m is the number of semesters. The PMS_{Ai} and PMS_{Bi} are the student number of student intake after and before using the PMS system at i^th semester, respectively. This equation summarizes the difference between student intake after and before applying the proposed PMS. Then the percentage improvement has been calculated.

VI. LIMITATIONS & FUTURE SCOPE

A computing system without limitation is either underexplored or unrealistic. Any physical or digital system in this universe always has limitations and weaknesses. The proposed HEI PSM system is not an exception. This section highlights the limitations of the proposed system. However, instead of limitations, they have been considered as the future scope of further development of this system.

A. FEEDBACK DEPENDENCY

Not everyone has time to write lengthy sentimental feedback. Out of 1200 feedback, 1050 were useful in the experimental phase. The excluded feedbacks were ambiguous or single word which carries no sentimental information. The proposed system depends on the stakeholder's feedback. If the feedbacks are not well-written, there is a probability of a wrong decision from the system. However, this limitation opens the door to conducting other research to classify the feedback into acceptable or rejectable categories. A separate module is trained to rank the feedback based on the quality of the feedback is a potential solution to this problem. Applying a reinforcement learning algorithm is another potential and even better solution to this limitation.

B. LACK OF GENERALIZATION

The proposed HEI PMS system demonstrates the acceptable performance of the experimenting institution. However, if the organizational structure changes, the admin user must redesign the user interface and create a new database table. Most importantly, the BiLSTM network needs to be retrained and re-analyzed. From this context, the proposed system lacks generalizability. A rigorous study of the structure of different institutional structures is necessary to prepare a generalized version of the proposed HEI PMS system. However, it is beyond the scope of this paper. That means it remains an open research field to explore in the future. A potential future direction of this research is creating a massive dataset collecting data from different institutions. Then sub-classifying these data according to the similarity among different HEIs. As a result, this dataset will become diverse enough to train a BiLSTM network which will be good enough to apply to higher educational institutions.

C. INCLUSIVE ANALYSIS

The effect of the proposed HEI PMS system has been analyzed while other marketing and promotional activities were still active. Discovering the proposed system's exclusive effect is beyond the scope. No institution will agree to pause its active marketing and promotional activity to facilitate an environment for HEI PMS system research unless they are provided with some subsidies. It is beyond the scope of this research project to allocate funds for such subsidies. This is a significant weakness of this paper. A potential solution to this weakness is developing a context-aware network to separate the proposed PSM from other marketing strategies. The context-aware network will store the effects separately whenever the promotional instruction is derived from the users' feedback. As a result, even though all marketing strategies run simultaneously, the effect of the HEI PMS system can be separated exclusively.

D. SHORT-TERM ANALYSIS

University admission rate varies based on various factors. Analyzing the proposed system for student intake improvement requires a three to five years observational period. However, experimental analysis was done over two year period only. It is another weakness of this study. However, an ongoing data collection process is running to observe the effect of the proposed HEI PMS system for three years. It will overcome the weaknesses of the current state of the paper in the future. The current analysis of the proposed PMS system has been done over 24 months. The data collected over the next 36 months will be used in the same system to identify the effects' differences. A marginal difference will indicate the robustness of the proposed PMS, and significant differences will indicate the scope of improvement.

The limitations and weaknesses of this paper offer new research opportunities. These opportunities will be availed to develop a better version of the proposed HEI PMS system.

VII. DISCUSSION AND CONCLUSION

The Higher Educational Institution (HEI) Promotional Management Support (PMS) system, which utilizes sentiment analysis to enhance student enrollment, is a groundbreaking application of artificial intelligence. The practical application of the PMS demonstrates the potential of significantly improve the student intake in HEIs. It has been derived by combining Emotional Intelligence (EI) and Artificial Intelligence (AI). The application of data analytics in marketing and sales is not new. There are many tools to visualize data and predict the sales rate. It is a data analytics-based decision support system. The proposed PMS system is the first paper that has taken the application of data to a different paradigm where EI is combined with AI to promote HEI. That is why it is a revolutionary system in the context of AI applications.

This innovative approach has elevated marketing strategies for HEIs, enabling the creation of marketing content designed to engage the target audience through emotional intelligence. This represents the first-ever use-case of sentiment analysis in this unique manner. This paper's data collection and processing methodology guarantees a feature-rich dataset for training the sentiment analyzer. Utilizing the BiLSTM network significantly enhances the overall efficacy and robustness of the process. The meticulously designed architecture, combined with the appropriate selection of an optimizer, ensures the exceptional performance of the sentiment classifier, which serves as the core of the HEI PMS system. The predictions generated by this network play a crucial role in the decision-making process within the HEI PMS system. The development and implementation of the BiLSTM network, underpinned by mathematical interpretation, solidify its position as a robust and accurate sentiment classifier.

The sentiment analyzer classifies the sentiment of the stakeholders with 92.75% accuracy. The average precision, recall, specificity, and F1 score are 0.9278, 0.9275, 0.9746, and 92.76, respectively. These values indicate the reliable performance of the BiLSTM network-based sentiment analyzer. The ROC-AUC curve shows that the sentiment analyzer has a 92.75% True Positive Rate (TPR) and a 7.25% False Positive Rate (FPR). It indicates that the proposed model accurately classifies positive and negative classes. The performance analysis of the BiLSTM network demonstrates its quality as an outstanding sentiment analyzer. Its accurate response is further reflected in the results obtained from the real-world implementation of the system. The observational data over two years shows a remarkable 4.78% improvement in student intake rate. The application of the proposed PMS system for HEIs is confided within the HEIs domain in this experiment. However, any organization can implement the proposed PMS system using the feedback of its stakeholders. Some potential applications are marketing strategy development for large-scale super-shop, showrooms, and shopping malls.

In conclusion, the Higher Educational Institution (HEI) Promotional Management Support (PMS) system represents a pioneering application of artificial intelligence, employing sentiment analysis to boost student enrollment. The innovative BiLSTM network-based sentiment analyzer at its core demonstrates exceptional performance, with an accuracy rate of 92.75%, as well as impressive precision, recall, specificity, and F1 scores. This groundbreaking approach has significantly enhanced marketing strategies for HEIs, facilitating the creation of emotionally intelligent marketing content tailored to engage the target audience. The real-world implementation of the system further validates its efficacy, with a notable 4.78% increase in student intake rate observed over two years. The HEI PMS system showcases the immense potential of sentiment analysis in driving positive outcomes within the higher education sector.

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