Received: 13 August 2022 | Revised: 21 September 2022 | Accepted: 10 October 2022

DOI: 10.1111/exsy.13172

ORIGINAL ARTICLE

Expert Systems WILEY

A predictive typological content retrieval method for real-time applications using multilingual natural language processing

S. Baskar[1] | Sunita Dhote[2] | Tejas Dhote[3] | Gopalan Jayanandini[4] | Duraisamy Akila[5] | Srinath Doss[6]

[1]Department of Electronics and Communication, Karpagam Academy of Higher Education, Coimbatore, India

[2]Department of Management Technology, Shri Ramdeobaba College of Engineering and Management, Nagpur, India

[3]Department of Mechanical Engineering - Engineering Mechanics, Michigan Technological University, Houghton, Michigan, USA

[4]Faculty of Architecture Design and Planning, Karpagam Academy of Higher Education, Coimbatore, India

[5]Department of Computer Applications, Saveetha College of Liberal Arts and Sciences, SIMATS Deemed to be University, Thandalam, Chennai, India

[6]Faculty of Engineering and Technology, Botho University, Gaborone, Botswana

Correspondence
S. Baskar, Department of Electronics and Communication, Karpagam Academy of Higher Education, Coimbatore, India.
Email: tobaskars@gmail.com

Abstract

Natural language processing (NLP) is widely used in multi-media real-time applications for understanding human interactions through computer aided-analysis. NLP is common in auto-filling, voice recognition, typo-checking applications, and so forth. Multilingual NLP requires vast data processing and interaction recognition features for leveraging content retrieval precision. To strengthen this concept, a predictive typological content retrieval method is introduced in this article. The proposed method maximizes and relies on distributed transfer learning for training multilingual interactions with pitch and tone features. The phonetic pronunciation and the previous content-based predictions are forwarded using knowledge transfer. This knowledge is modelled using the training data and precise contents identified in the previous processing instances. For this purpose, the auto-fill and error correction data are augmented with the training and multilingual processing databases. Depending on the current prediction and previous content, the knowledge base is updated, and further training relies on this feature. Therefore, the proposed method accurately identifies the content across multilingual NLP models.

KEYWORDS
content retrieval, knowledge base, natural language processing, transfer learning

1 | INTRODUCTION

Multilingual is using various languages to express certain things among people. A multilingual is someone who uses many languages to speak. Multilingual natural language processing (NLP) is used in various applications. Multilingual NLP guides the network or system to build an efficient and feasible system (Wang et al., 2022). NLP is mainly used to process data that provide a necessary function to process language via computers. There is a significant role for multilingual processing based on NLP in strengthening services and systems. Linguistics, computer science, and math techniques are used in multilingual NLP systems (Wajsbürt et al., 2021). When applied to languages, NLP uses a predetermined set of operations and functions to zero down on the most salient characteristics and patterns of each language (Edmonds, 2020). NLP is implemented in the multilingual system to perform analysis, recognition, detection, verification, modelling, and designing of the redundancy of languages. Various toolkits and algorithms are used in multilingual NLP systems. The lightweight transformer-based toolkit is commonly used for multilingual NLP systems (Boros et al., 2022). The system's overall performance is improved using a transformer-based toolkit since it boosts efficiency and decreases latency. The software begins by determining the text's structure, language pattern, meaning, and examples. Using NLP across many languages improves the reliability of detection and recognition (Litschko et al., 2022).

Typology features are one of the linguistics fields that identify and classify languages based on structural features and patterns of language. By providing concrete information about a language, topology features help reduce false positives during the identification and detection stages

(Li et al., 2019). Typology features, also known as linguistic topology, first study the patterns and texture of languages. Detecting typology features in an application is a challenging process. NLP is widely used in the typology feature detection process. NLP analyses the details and meaning of language using grammatical features (Yusuf et al., 2019). The latency rate during identification can be decreased with features that supply a suitable data set for the detection process. Without the need for pre-existing "pipelines" or "techniques," NLP can detect linguistic patterns and features (Cai et al., 2019). The topology detection technique uses feature extraction to learn crucial linguistic information. The detection procedure is improved by the optimal collection of information produced by the extracted data (Wang & Zhang, 2020). Topology data analysis is also used in the detection process that analyses the missing details and features of languages. A geometric toolkit is used in the analysis process to find the missing topology features from the database (Qiu et al., 2020).

Typological errors are occurred due to specific changes in patterns and textural features of information or content. The typological error causes various problems in an application that reduce the flexibility rate of the system. Accurate content retrieval is a challenging process for any software (Solainayagi & Ponnusamy, 2019). Human-constructed graph technique is commonly used in the content retrieval process. The graph approach pinpoints the precise topological defect and generates a usable data set for further investigation. In this case, the classification procedure is used to organize the data stored in the database (Shiah, 2020). Precise content retrieval provides appropriate and mission features for the NLP system. Before any information about the contents can be retrieved, the retrieval method must first identify certain descriptions and linguistic patterns (Li et al., 2020). NLP uses both physical and logistic content retrieval procedures, which improves the system's practicability and reliability. The process of content retrieval for NLP systems also makes use of machine learning (ML) techniques and algorithms. ML technique uses the regression method to identify the exact meaning and whereabouts of information presented in the database (Chen et al., 2021; Meesad, 2021).

This paper is structured as follows: The description of related work and its accompanying debate is found in Section 2. Section 3 discusses the predictive typological content retrieval method (PTCRM) for training interactions with pitch and tone features. The findings and forum from Section 4 have been compared to a previously developed approach. The investigation is research scope will be closed in Section 5, examining the subsequent research scope and future scope of research.

2 | RELATED WORKS

Ait-Mlouk and Jiang (2020) developed a chatbot powered by a knowledge network for use in NLP. The suggested chatbot relies heavily on ML approaches to decipher the system's language. The proposed approach can decipher the precise significance of user interaction and shared content. To determine which terms are included in a given dataset, a knowledge graph can be used. The proposed approach improves both the adaptability and practicality of the system.

Sun et al. (2021) a multi-agent boundary-aware network (MABAN) was proposed to retrieve moments from natural languages (NLMR). The distance regression method is used in MABAN to reduce the temporal boundaries presented in the retrieval process. The MABAN system uses a multi-agent reinforcement algorithm to decipher the available temporal meaning in a conversation. MABAN improves the accuracy rate in the moment retrieval procedure to its highest possible level. To improve NLMR's efficacy and efficiency, the authors propose a MABAN.

Nishimura et al. (2019) presented an approach to machine translation based on neural networks. Finding data gaps is the primary use of the suggested technology, which improves translation accuracy. For the translation process to succeed, missing data are essential to improve the system's efficiency and practicality. NMT can identify meaning and structure across several languages, which helps to lower the error rate during computation. There is a significant improvement in translation accuracy using the proposed NMT.

El-Alami et al. (2022) proposed a multilingual offensive language detection (MOLD) method for social media. Bidirectional encoder representation from a transformer is used in MOLD to identify the available content on social media. A classification method in MOLD classifies the information based on the texture and meaning of languages. The proposed MOLD approach improves the detection accuracy rate, decreasing the number of unneeded issues on social media.

Roostaee et al. (2020) presented a fusion approach to identify plagiarism across languages. The fusion approach uses conceptual and keyword-based approaches to address many issues by employing multiple languages. Information keywords and ideas relevant to detection are compared in the suggested fusion approach. As a result of using the proposed method, the system's efficiency and robustness are both much enhanced, as is the rate of accuracy achieved in the cross-language detection process.

Cui et al. (2022) presented an approach to analysing a model of machine reading comprehension (MRC) from multiple perspectives. The study additionally uses a pre-trained language model (PLM), which boosts the system's efficiency. Users' intended meaning and information can be deciphered with the help of the proposed technology. Language compatibility issues, such as PLM, help alleviate some computation-related issues. When applied to MRC systems, the proposed technique improves efficiency and dependability.

Interdonato et al. (2019) enhanced a lightweight crisis management framework based on Twitter data. Twitter data are collected during a particular set of crises that occurred on social media. Twitter's data provide the information required for data extraction and analysis. The suggested method utilizes unsupervised extraction to glean the features and information from Twitter data. The recommended approach expands the system's adaptability and practicality.

Enamoto and Weigang (2021) created a multilingual short text classification framework (GM-ShorT). To gather the required information for GM-ShorT, the suggested system uses the convolutional neural network (CNN) method. To get the most out of a dataset, CNN employs a feature extraction technique to pull out the most relevant information. GM-ShorT classifies short text messages and their context to deliver relevant services to the users. The proposed GM-ShorT improves the system's efficiency by raising the accuracy rate of the categorization process.

Ye (2021), an English language intelligent retrieval method, was introduced for wireless sensor networks (WSN). In this case, WSN is employed to amass data necessary for retrieval and to generate a superior data set for subsequent analysis and detection. The proposed strategy optimizes the accuracy rate of the retrieval procedure. The proposed approach improves the efficiency of the system since it decreases the rate of time and energy consumption during the retrieval process.

Ma et al. (2022) a text visualization approach for geological hazard reports was proposed. Improved system stability is achieved using a combination of NLP and data mining techniques employed in the visualization approach. Features and information of importance are extracted via NLP. Here, data mining is employed to categorize the data according to a predetermined set of data and information. Regarding system performance and feasibility, the proposed approach is superior to alternatives.

De la Rosa et al. (2021) introduced a multilingual pattern prediction method for NLP. The transformer model is used here to understand the exact meaning and content of messages transferred by the users. An optimal data set for the prediction process is generated once a system has detected metric patterns. The process of prediction relies on reliable data collection that conveys the intended meaning of the text. The proposed strategy improves prediction accuracy while decreasing computational and analytical delays.

Kanfoud and Bouramoul (2022) a novel representation strategy for multilingual sentiment analysis was developed. An algorithm deciphers the sentiment codes and generates a workable data set for the detection procedure. Multilingual features and patterns are extracted from a data collection to provide relevant information for the detection procedure. Experiment results validate that the proposed method improves the analysis's accuracy rate, boosting the system's performance and feasibility.

Kamper et al. (2021) introduced a word embedding model using multilingual transfer for zero-resource languages. The proposed model first trains the dataset necessary for the prediction process. Correspondence autoencoder (CAE) is also used in the embedding model to find the exact meaning of interaction and contents. By speeding up the computation process, CAE boosts the system's reliability. By boosting identification accuracy, the suggested embedding model makes the system more trustworthy and effective.

Pająk and Pająk (2022) proposed a multilingual fine-tuning method for grammatical error correction (GEC). NLP is used here to find the exact meaning of language via the feature extraction process. The language's patterns and features are isolated in the feature extraction phase, yielding the best possible data for the tuning phase. The necessary dataset for GEC is trained with pre-trained multilingual models. Error rates in several languages can be reduced thanks to the proposed method's improved GEC quality.

In general, NLP or computational linguistics is the emerging multidisciplinary discipline to embrace the sophisticated analysis tools of ML and statistical methods. Transfer learning, hidden Markov models, support vector machines, and deep learning are some of the most popular methods used to tackle different NLP challenges using distributed learning methods. These methods highlight the ambiguity in speech and language processing, provide a brief overview of basic categories of linguistic knowledge, and finally provide a comprehensive review of various state-of-the-art ML models for prediction and analysis.

NLP uses Transfer Learning to quickly train a model to predict the sentiment of a phrase by taking a trained model and removing the layer that predicts the next word and replacing it with a new layer. However, it does seem to capture a lot of relevant information in a sentence when processing and transforming into rich representations, which are fed into the last layer to predict the next word. To improve the accuracy of content retrieval, multilingual NLP needs extensive data processing and interaction recognition characteristics. The PTCRM utilizes reinforcement for training interactions across languages with pitch and tone data to determine specific contents from prior processing instances, which has been considered a significant contribution to this research.

3 | PROPOSED CONTENT RETRIEVAL METHOD

NLP from human voice recognition through computer aided-analysis is to leverage content retrieval precision based on interaction recognition features, and vast data processing requires multilingual NLP. The challenges in multilingual NLP models, precision content retrieval, and error occurrence are the available features satisfying the human voice of different users. The human voice is recognized through receiving device and requires distributed processing system for NLP. Therefore, regardless of the interactive input from the human voice, multilingual input voice recognition is a prominent factor. The proposed PTCRM focuses on this factor for understanding human interactions based on a processing system through a human voice-receiving device. This proposal is reliable in identifying the content across multilingual NLP models with the available processing system. From this human voice recognition, the knowledge base (KB) stores interactive input voice as a record through receiving device and has been recognized to expedite communication and reduce communication errors. This proposed work improves the quality of phonetics in record systems that hold the automatic error correction and train the data prediction by updating the KB. One of the most significant benefits of NLP is to develop improved system architecture by which computers can extract meaningful information from human language to improve their ability to communicate with humans. Additionally, human–computer interaction (HCI) applies the principles of signal processing and cognitive science to the design of interactive computer systems to facilitate interactions through computer aided-analysis. The ultimate goal is to increase the prevalence and ease of use of HCI with the transfer learning process.

The proposed method is portrayed in Figure 1.

Distributed transfer learning is used to maximize the training for multilingual interaction through pitch and tone based on phonetics. The PTCRM method balances the pitch and tone through interactive input of the human voice. In this proposed method, prediction and precise content of the real-time applications are easy for achieving reliable output for precise content retrieval. Instead, the design goal of this method is to observe error-less phonetics prediction and to maximize the available processing system. The proposed method functions two processes (i.e.) precision content retrieval and error mitigation concurrently. In this research, a transfer learning strategy has been used for mispronunciation detection using PTCRM to exploit the training for multilingual interaction. Instead of training the whole network with PTCRM, transfer learning is employed with hidden layers taken from NLP to spot instances of incorrect pronunciation for precise content retrieval. In the first step, phonetic-discriminating features are extracted using the hidden layer. In the second phase, a trainable knowledge-based layer is utilized to assimilate precision content retrieval and error mitigation concurrently. The audio models are trained according to various criteria, and the validation is performed by experimenting with various architectures for mispronunciation detection. The precision content retrieval is based on prediction and KB to handle the multilingual NLP models. The initial function of the interactive input observed from the human voice is important to the objective, as given in Equation (1).

$$\left.\begin{array}{l} \underset{\text{in} \in t}{\text{maximize}}\; H_v \forall\, P_c = T_o \\ \text{Such that} \\ \underset{\text{in} \in T_o}{\text{minimize}}\; ER_m \forall\, P_c \\ \text{where} \\ ER_M = p_{P_c} - p_{T_o} \\ \text{and} \\ \underset{\text{in} \in t}{\text{minimize}}\; M_{\text{NLP}}\ \forall\, \text{in}_r \in\ P_c \end{array}\right\} \tag{1}$$

In Equation (1), the variables H_v, P_c, T_o, and t represent interactive human voice input, pitch, tone, and processing time based on input recognition of a in number of voices observed at t time intervals, respectively. In the next processing system, the variables ER_M, p_{T_o}, and p_{P_c} denotes error mitigation, processing pitch, and processing tone observed for input voice, respectively. The third objective of minimizing the multilingual NLP model is representing using the condition $M_{\text{NLP}} \forall \text{in}_r \in P_c$. If $f = \{1, 2, ..., f\}$ represents the different features observed in input voice recognition, then the

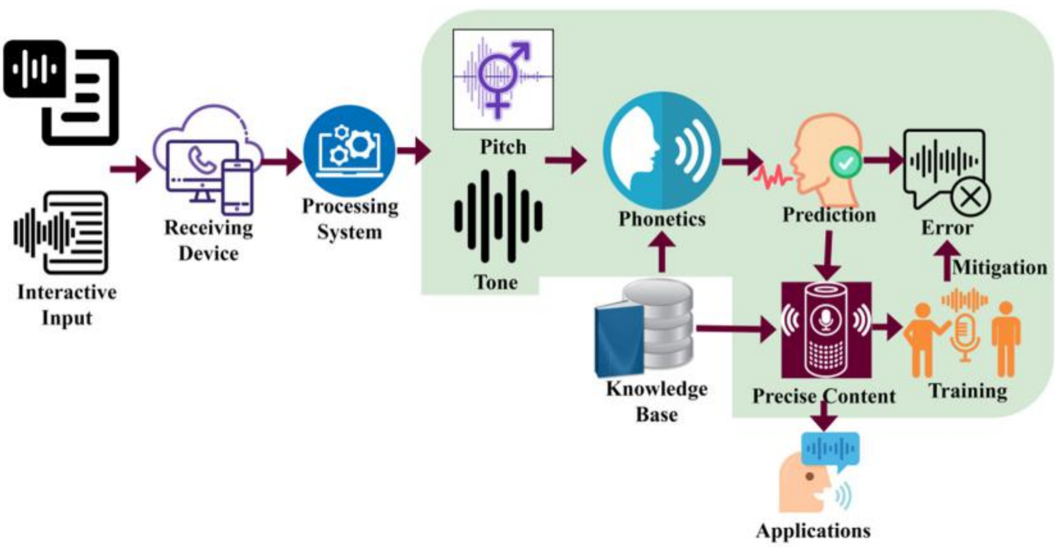

FIGURE 1 Proposed method

number of receiving device analyses in the processing system (ps) is $P_c \times t$, whereas the voice pitch is $f \times P_c$. Based on the total voice pitch of $f \times P_c$, $t \times P_c$ are the serving input for input voice recognition. The vast data processing and interaction recognition features are reliable using content retrieval precision based on the input voice pitch. In this processing system, input recognition of pitch and tones is essential to identify the phonetics of additional data prediction. The phonetic pronunciation is the capacity (Ph_n) of the n input recognition; the processing system needs to predict and classification for the multilingual interactions to improve precise content retrieval. The prediction and classification of the voice recognition based on the available n are performable using distributed transfer learning paradigm. Later, depending upon the prediction, the precise content analysis is the augmenting feature. For the prediction process, phonetics pronunciation is the prevailing instance for determining different data predictions. The precision control retrieval from the previous content-based prediction for pitch and tone is important in the following manner. In this prediction process, the multilingual NLP of $(P_c \times t)$ for all n using knowledge transfer based on Ph_n is the considering factor. The probability of prediction (ρ_p) based on the continuous process is given as

$$\left.\begin{array}{l} \rho_p = (1 - Ph_n)^{in-1} \forall \text{ in} \in t \\ \text{and} \\ Ph_n = \left(1 - \dfrac{P_c \in n}{P_c \in t}\right) \end{array}\right\} \tag{2}$$

In Equation (2), the continuous processing system follows the compact probability of n such that there is no input recognition. Hence, the precise content retrieval is computed as in the above equation. Therefore, the prediction of phonetics for ρ_p follows

$$\text{Precise content } (n) = \frac{1}{|T_o - P_c + 1|} \cdot (\rho_p)_{\text{in}} \forall \text{ in } \in t \tag{3}$$

The prediction for n phonetics as in the above equation is valid for both voice pitch and tone recognition, ensuring processing systems. The converging process of interactive input processing of assigning t instances to reduce the communication errors based on the condition $(f \times P_c) > (t \times P_c)$. The phonetics are descriptive using the prediction process. Therefore, the precise content retrieval is $f > t$, and phonetics is less to satisfy Equation (1). The contrary output for the above condition is the prolonging phonetic pronunciation and hence the knowledge transfer, resulting in error mitigation and training. The error mitigation process is illustrated in Figure 2.

The input pitch and tone from the human voice input are analysed using the stored ones. From the verification through t, the ρ_p is estimated as in Equation (2) for differentiating $|T_o - \rho_C|$ (consistent) and $|T_o - \rho_c + 1|$ (varying). The completely non-matching $(f \times \rho_C)$ is classified as an error such that it does not hold for Equation (1)'s objectives (Refer to Figure 2). In the error mitigation process, the unbalancing condition of $f > t$ is high, and hence the prediction of phonetics thorough KB. Along with the interaction recognition of n, the precise content and error mitigation is the considered metrics here. The probability of error mitigation (ρ_{ER_m}) is given as

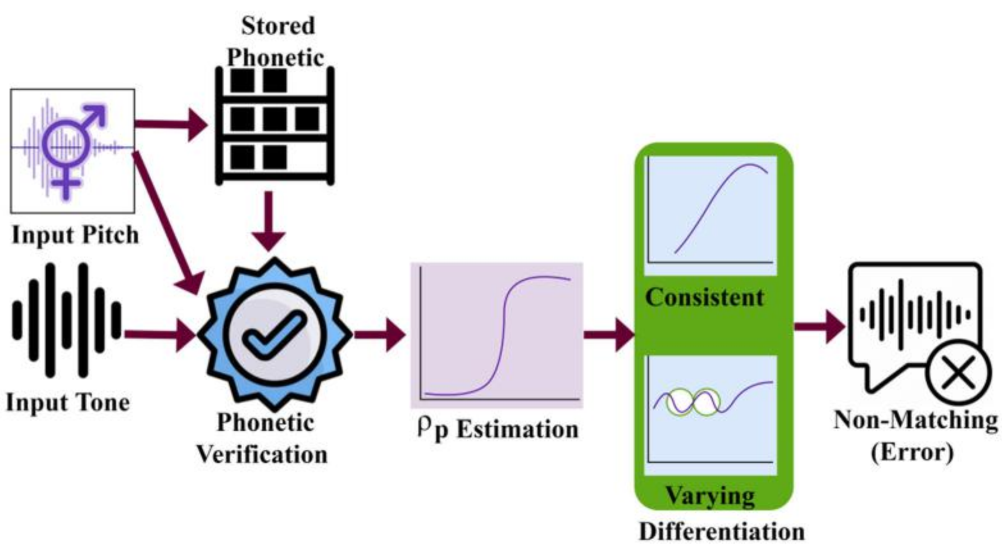

FIGURE 2 Error mitigation process

$$\left.\begin{array}{l}\rho_{ER_m}=\dfrac{\rho_p.\text{Precise content }(n).[(P_c-T_o)Ph_n]}{F(\alpha).N}\\ \text{where,}\\ F(\text{Mul}_{\text{int}})=\displaystyle\int_0^t M_{\text{NLP}}(1-M_{\text{NLP}})^{t-1}dt\\ \text{and}\\ F(\text{Mul}_{\text{int}})\in\text{Precise content }(n)=\displaystyle\int_1^{P_c} M_{\text{NLP}}{}^{t-1}.\frac{Ph_n}{n}(1-\rho_{ER_m})^{t-1}dt\end{array}\right\} \tag{4}$$

In Equation (4), the variable $F(\text{Mul}_{\text{int}})$ denotes the function for multilingual interaction at different time instances t. For all the phonetic predictions, the error mitigation in recognizing voices based on n intervals is a communication error. The prediction, as in the above condition, requires more pitch and tones, thereby increasing the multilingual interaction. Based on the analysis, the prediction-based error mitigation processed based on $f > t$ and n phonetics and data predictions are the considered factors. Distributed transfer learning can be used to address these issues by sharing knowledge and thereby reducing the likelihood of miscommunication. This section next presents the phonetics-based prediction used to reduce the number of mistakes.

Precise content retrieval using prediction: The process of classifying precise content retrieval relies on the distributed transfer learning process. It aids content retrieval for both phonetic pronunciation and the previous content-based prediction. The phonetics and data prediction based on precise content retrieval provide training through the KB instances using applications. The prediction relies on different pitches and tones for analysing the error mitigation and training probability instances during interactive input voice processing. Hence, the condition for voice recognition varies, which follows phonetics information through prediction. The content retrieval is illustrated in Figure 3.

For training interactions across languages with pitch and tone data, the transfer learning technique extensively uses transferred information that includes phonetic pronunciation and the preceding content-based predictions. Using a distributed transfer learning model, the accurate predictions and classifications for speech recognition are processed. TL helps to improve Phonetic pronunciation for precise data predictions during the prediction process and detects errors in communications resulting from massive data processing and interaction recognition based on the accuracy of content retrieval. The consistent $\rho_p \forall$ the H_v Classified is used for recognizing the required content. The knowledge-based matches the available and ρ_p features for identifying the content till n. Depending on the content, the retrieval is verified throughout the $n \forall t$ such that $|T_o-\rho_C+1|$ is not present. This post-process is performed for the knowledge-based update to improve retrieval (Refer to Figure 3). Distributed Transfer learning and knowledge transfer have identified the challenge of adapting the insights learned from one problem-solving endeavour to another as a distinct research subject. The prediction based on phonetic pronunciation is prescribed for pitch and tone analysis by computing the n processing system probability and precise content retrieval of voice input for training multilingual interactions. The first prediction relies on maximum multilingual NLP t and $F(\text{Mul}_{\text{int}})$ is given as

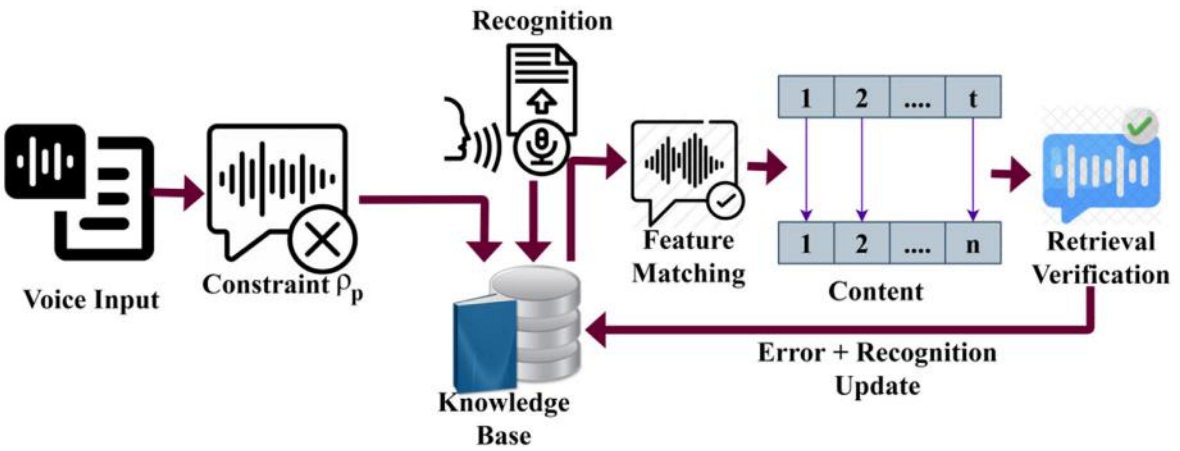

FIGURE 3 Content retrieval process illustration

$$\left.\begin{array}{l} F(\mathrm{Mul_{int}}, t) = \left[T_o - \left(\frac{ER_m}{p_{P_c}}\right) \times \frac{1}{n}\right] - \text{Precise content } (n) + 1 \\ \text{such that} \\ \sum_{in \in tin \in P_c} \sum t_{\mathrm{in}} - \sum_{in \in T_o} Ph_n \\ \text{and} \\ n = \sum_{in \in t} \text{Precise content } (n) - (Ph_n)_{\mathrm{in}} \end{array}\right\} \tag{5a}$$

Using the above Equation (5a), the multilingual NLP depending the prediction of the phonetics as in ρ_{ER_m} and Precise content(n). Here, the chances of continuous voice recognition are computed as

$$\left.\begin{array}{l} \rho_{ER_m}(t) = \frac{1}{\sqrt{2n\pi^2}}\left[-\frac{P_c - Ph_n \times T_o}{\pi}\right] \\ \text{where, } \pi = P_c - Ph_n \times n \end{array}\right\} \tag{5b}$$

In the above prediction computation, the main goal is to equalize f and t to reduce the communication error; hence; the actual voice tone is given as

$$T_o = \max\left[\frac{\rho_{ER_m} \times P_c}{\text{Precise content } (n) - Ph_n}\right] \tag{6}$$

Therefore, the precise content is $\left[1 - \frac{\rho_{ER_m} \times P_c}{\text{Precise content } (n) - Ph_n}\right]$ and this content retrieval is the training instances based on pitch and tones. The exceeding pitch and tone $[P_c \times F(\mathrm{Mul_{int}}, t)]$ is the error occurrence instances, and hence the multilingual interaction increases. There are two possible instances for increasing the multilingual NLP model in human voice recognition per Equation (5b). This input voice recognition is given as

$$\text{Min Possible } T_o = \pi = P_c - Ph_n \times n$$

max possible is computing RHS of equations (5b) and (2)

$$\left.\begin{array}{l} (1 - Ph_n)^{\mathrm{in}-1} = \frac{(T_o + Ph_n.P_c)}{\sqrt{2n}\pi^2} \forall \text{ in} \in t \\ T_o = Ph_n P_c - (1 - Ph_n)^{\mathrm{in}-1} \\ \text{If } Ph_n = 0, T_o = \sqrt{2n}\pi^2 = \sqrt{2n}\ (P_c)^2 (\min) \\ \text{If } Ph_n = 1, T_o = P_c\ (\max) \end{array}\right\} \tag{7}$$

In Equation (7), the output of precise content retrieval (as per the pitch and tone) is either of π (or) T_o for both instances, if $Ph_n = 0$, then $\pi = P_c = T_o$ are the maximum multilingual interactions, and if $Ph_n = 1$, $P_c = T_o - n$ or $P_c = T_o$ is the minimum multilingual interaction. Therefore, the content retrieval of $P_c = T_o$ is an optimal result where the interaction recognition and vast data processing for all the pitch analyses are given in the above equation. The learning for maximizing precision is illustrated in Figure 4.

The actual n contents are validated for ρ_p across t such that T_o and $\mathrm{Mul_{int}}$ are forwarded. If the forwardings are precise, then recognition is improved. Contrarily, if $T_o < P_c$ then ph is observed, $(\rho_{ER_m} - Ph_n)$ is the actual precise content. This is maximized for $T_o = P_c$ condition preventing $(n - P_c)$ Occurrences (Figure 4). The input voice recognition in this scenario for all n instances, where pitch and tone are equalizing, and the content retrieval is idle as in Equation (1). The phonetics based on prediction $(P_c - Ph_n \times n)$ and $\sqrt{2\pi}(P_c)^2$ a condition that determines the training data and precise contents (along with error mitigation) for equalizing pitch and tone. The prediction is based on the conditions $(P_c - Ph_n \times n)$ and $\sqrt{2\pi}(P_c)^2$ from the available instance $t \in P_c$, respectively. The prediction process classifies precise content and error mitigation based on requiring t from the processing system. The probability of pitch, tone, and phonetics are the considered factor for both instances of prediction using the KB. The automatic correction of error identification based on equalizing pitch and tone is computing based on t for $F(\mathrm{Mul_{int}})$ is given as

$$\text{Precise content } (n) = \begin{cases} \frac{n - (Ph_n \times P_c)}{n + (\rho_{T_s})P_c} \forall\ T_o = P_c \\ \frac{n - (\rho_I \times P_c)}{n + (\rho_{ER_m} - Ph_n)P_c} \forall\ T_o < P_c \end{cases} \tag{8}$$

In Equation (8), the prediction instances and error mitigation $(\rho_{ER_m} - Ph_n)$ is identifiable using Precise content(n). Hence, the actual pitch and tone in available phonetics the rest of the pitch for prediction, the pending voice inputs process until the next precise contents. The phonetics prediction process follows either pitch or tone equalizing as in Equation (8). It varies for both the pitch and tone analysing instances as the first input recognition for all n sequences. Whereas the second input recognition requires previous precise content retrieval as $(n-P_c)$ is the retaining pitch. As per the prediction in the previous section, phonetics is based on a KB for $ER_m \in P_c = \frac{(n+1)T_o}{n}$ is reliable in precisely identifying content retrieval, and it does not require communication error. From the Equations (1)–(6), this empirical research and the mathematical formulation validate the connection among informational interactions between phonetics, phonology, and the lexicon, the three classic language modules. For instance, the phonetic qualities of a word's sounds are affected by how often it is used; high-frequency words tend to be elongated in comparison to low-frequency ones. This collection of findings can be explained using precise content retrieval using prediction, depending on the type of analysis being performed, pitch or tone, the initial recognition might be different for each of the possible sequences has been validated in this research. The human voice processing system based on prediction and precise content is analysed in the multilingual NLP model consecutively depending on pitch and tone. Therefore, communication errors occurred in content-based prediction analysis are forwarded using the knowledge transfer. That is identified as errors in the prediction; the vast data processing and interaction recognition feature observed from the applications based on input voice recognition analysis improve the multilingual interactions to reduce the communication error at different intervals. Classification of matching and unmatching characteristics is carried out based on the phonetics validated based on the PTCRM. Each input is analysed using distributed transfer learning and the accuracy of prediction using real-time settings based on the multilingual phonetics. Here, the error is minimized on the basis of the prediction probability derived from several training cases.

4 | PERFORMANCE ASSESSMENT

The proposed method is analysed using the dataset from https://data.world/idrismunir/english-word-meaning-and-usage-examples containing 13,000+ English words and their meaning. A word is provided with 5–10 meanings for fulfilling a sentence using the autofill function. The synonym is provided using nine examples and a total of 11 columns. From this data, 100 inputs and 300 interaction sessions span are considered. The metrics of prediction accuracy, retrieval accuracy, feature extraction, retrieval time, and error are considered in light of the experimental study. As part of the examination, current approaches are compared to $FC+KS$ (Roostaee et al., 2020), lightweight crisis management framework (LWCMF), and MABAN (Sun et al., 2021) are considered. The application design is preceded as presented in Figure 5. Voice recognition from the

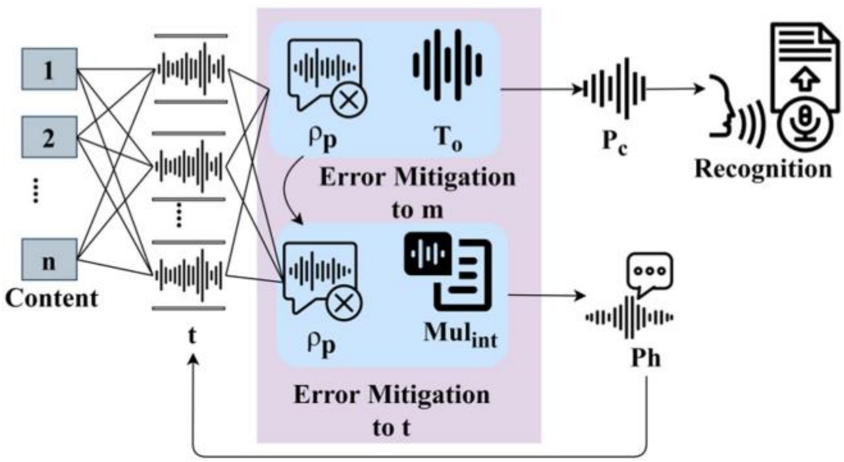

FIGURE 4 Learning for precision maximization

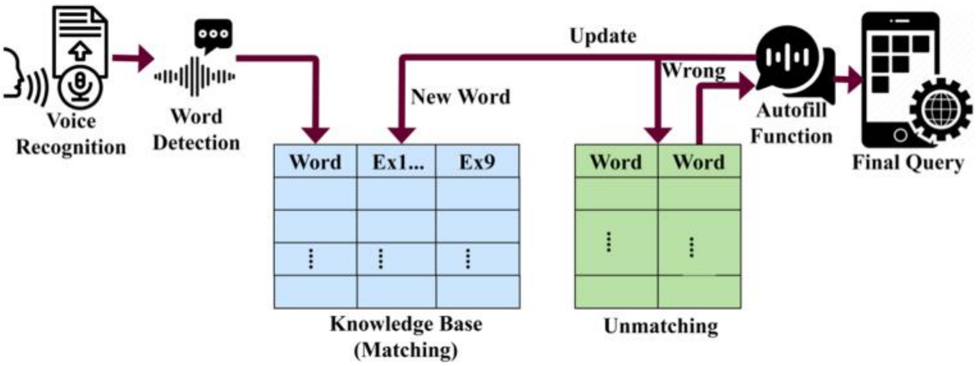

FIGURE 5 Application process

hand device is used for recognizing the word from data set inputs. A word is trained for 5–20 s and four trials based on different phonetics. The KB is updated using two instances, namely matching and un-matching contents.

The KB is distinguished as matching and unmatching for filtering the word (detected). If the final query matches the KB, it is provided. Contrarily, the precise possibilities are augmented (new) in the KB as updates. The unmatching detections are stored separately to prevent errors (Refer to Figure 5). This matching process for the classification and content retrieval is presented in Figure 6.

The precise content retrieval process relies on the T_o and P_c of the inputs from four different trails. The autofill function shows up distinct considerations based on the identified phonetics. If the identified word is present in the KB, then similar phonetics verification is performed. Contrarily for a new word, the user inputs the phonetics, whereas, for an unidentified word, it is ruled out. The prime process of $(P_c - Ph_n) \forall n \in$ the classification is performed for independent verification. Based on the different suggested outputs, the user selects the optimal one. This increases the precision provided $ph_n = 1 \forall T_o = P_c$ is maximized. Contrarily, the unselected word is used for further training through KB update (Refer to Figure 6). In Figure 7, the precise content (n) for the varying ρ_p and features are presented.

As the independent features through stored classification increase, the content retrieval is maximized. For the varying t, ρER_m is restricted for improving recognition. Depending on the H_v phonetics, the features are varied; the varying features increase the content retrieval accuracy $\forall \rho_p$ (Refer to Figure 7). Figure 8 illustrates the $\rho ER_m \forall \rho_p$ they were observed for the varying inputs.

In general, as the inputs vary, error varies. This is due to $F(\mathrm{Mul_{int}})$ for improving content retrieval accuracy. In this process, the error-causing factors due to T_o, Ph_n and $f > t$ are addressed through further classification. The learning instance reverts the updates between matching and unmatching features without increasing $|T_o - \rho_c + 1|$, confining the errors.

4.1 | Prediction precision

In Figure 9, the understanding of human interactions through computer aided-analysis of interactive input voice observed from human recognizes and processes through multilingual NLP models identifies precise content. The solution based on receiving device and processing system in precise content retrieval is to improve the automatic error correction. Different intervals of time for input recognition through the KB do not give

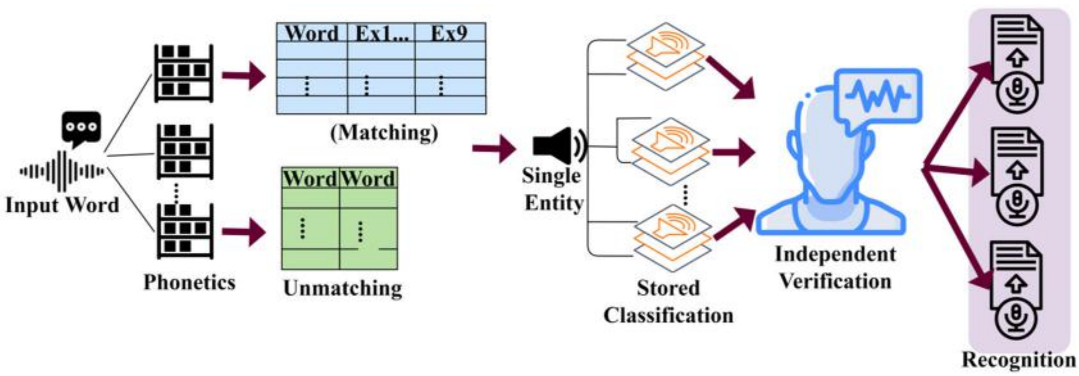

FIGURE 6 Matching process

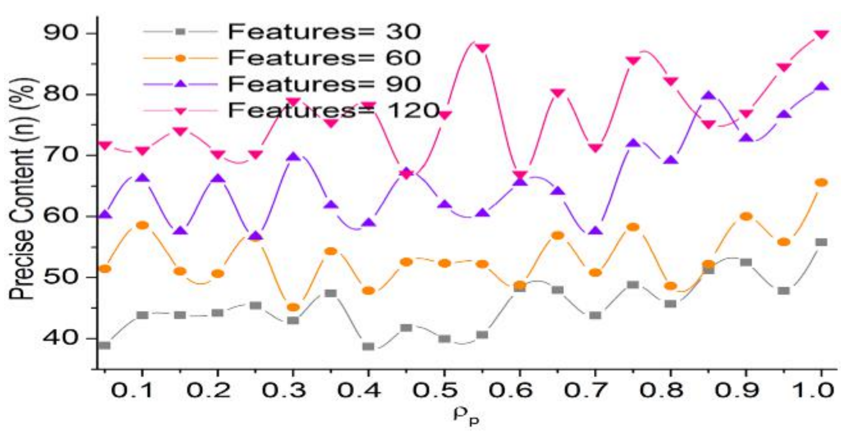

FIGURE 7 Precise content (n) for varying ρ_p

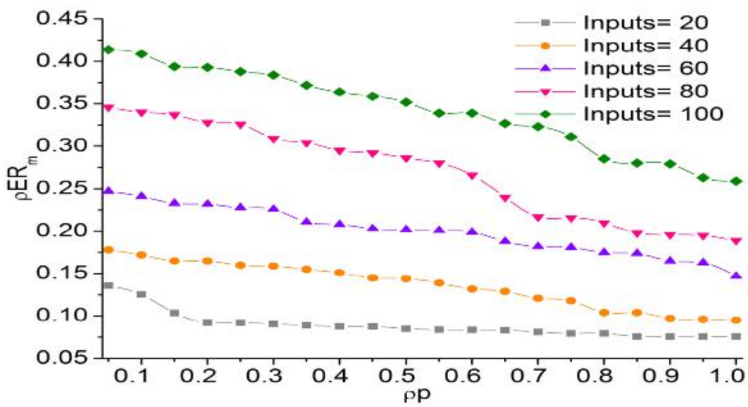

FIGURE 8 ρER_m for varying ρ_p

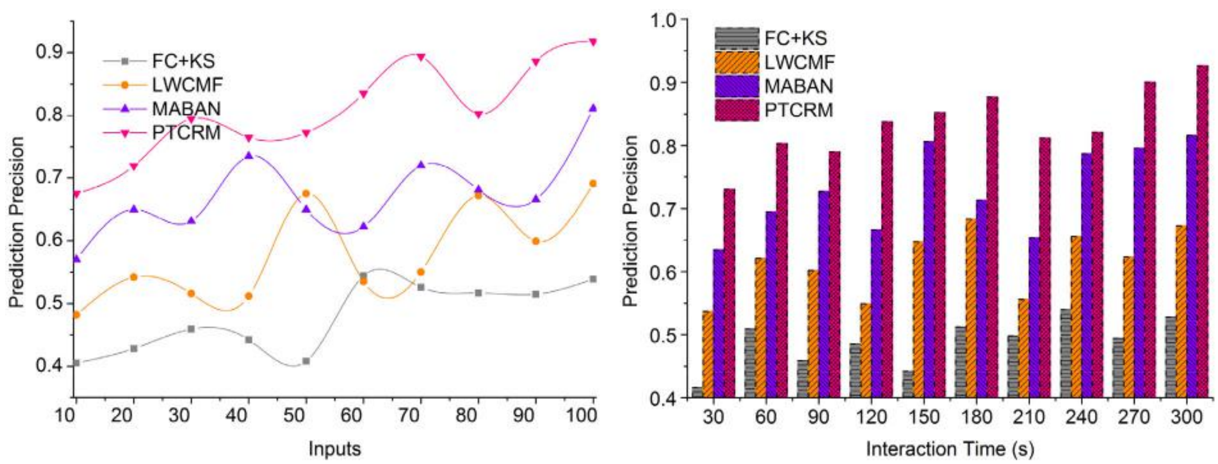

FIGURE 9 Prediction precision comparisons

phonetics for extracting the features and equalizing pitch and tone. Training multilingual interactions and detecting and mitigating errors, using a distributed transfer learning process based on $M_{NLP} \forall in_r \in P_c$. The previous content-based predictions from the first processing system performance of phonetics enhance the prediction precision. This prediction is analysed based on pitch and tone features, wherein the KB update is based on error mitigation during prediction. Using a distributed transfer learning model, the accurate predictions and classifications have been validated based on content-based prediction analysis. The accurate content analysis helps to enhance the feature based on the prediction analysis. From Figure 9, the phonetic pronunciation is the most common basis for determining distinct data predictions during the prediction process, which is validated based on PTCRM. Distributed transfer learning helps to optimize the precision control information to improve the pitch and tone based on the prediction procedure. The identified inaccuracy is corrected by retrieving the exact content of training data so that it can be processed to provide subsequent training for updating the KB. Therefore, the input recognition of human voice processed through training data prediction ensures error mitigation is reduced, preventing high prediction precision based on new training.

4.2 | Retrieval accuracy

The processing system performance is analysed for different feature extraction based on predictions to ensure precise content retrieval for its voice interaction at different periods. The error occurrence can be identified with the training instance and multilingual processing database based on real-time voice recognition applications. Human voice recognition relies heavily on being able to recognize and interpret subtle changes in pitch and tone in the initial serving of interactive input. This forecast is used to educate and better equip multilingual encounters. Phonetics based on Precise content(n) The condition addressed for the input human voice recognition is denoted in Figure 10. By computing the sequential data predictions based on phonetics in applications, the proposed PTCRM achieves high retrieval accuracy and training for multilingual NLP. Thus, the training and data prediction process is optimized through accurate content retrieval and a comprehensive KB. High retrieval accuracy using NLP is achieved with extensive training data and specific content in input recognition.

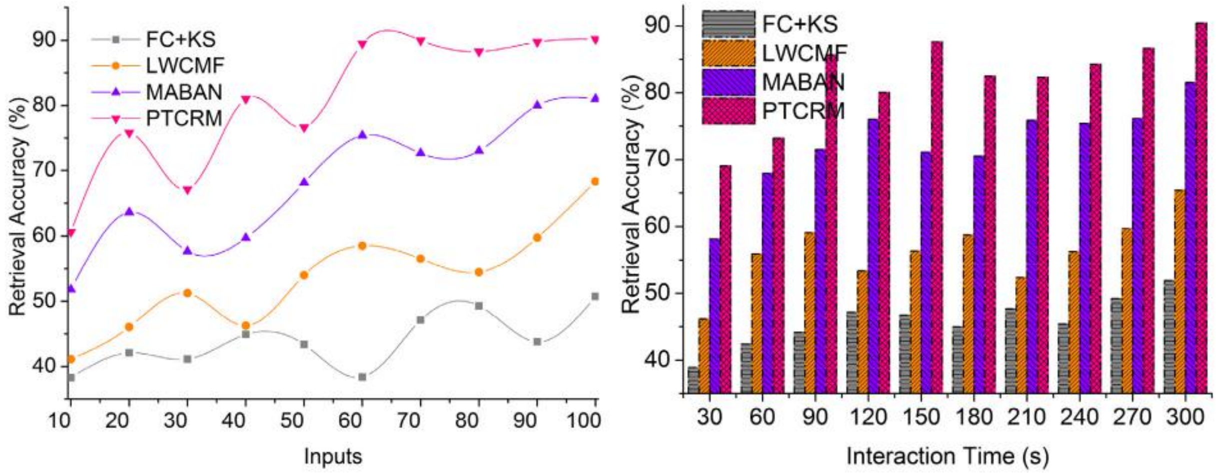

FIGURE 10 Retrieval accuracy comparisons

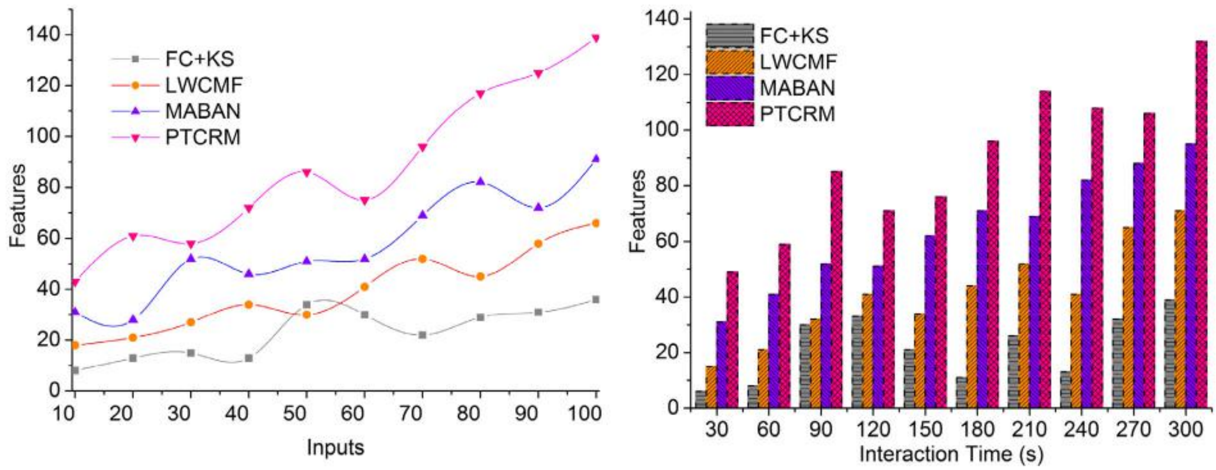

FIGURE 11 Feature extraction comparisons

4.3 | Feature extraction

Because it relies on interactive input processing and comparing prior content-based prediction observation with the current prediction, the suggested content retrieval approach for multilingual NLP models through a processing system provides high phonetic pronunciation and training. To improve the KB, we examine how well we can spot and correct for errors based on predictions made at varying intervals of time (Refer to Figure 11). Input speech recognition is handled phonetically, which helps reduce the sequential method of detecting content retrieval instances and multilingual interactions based on pitch and tone. Using the training data and the precise content, the feature extraction of additional training instances based on data prediction is used to identify communication errors. Knowledge transfer at varying intervals is used to improve the precision of content retrieval. Feature extraction based on training data prediction is analysed and recognized for training for updating error occurring content retrieval from the previous processing instance. Therefore, the feature extraction is high.

4.4 | Retrieval time

This proposed method for voice recognition and auto-fill and typo-checking applications are analysed through distributed transfer learning to identify communication errors based on prediction. The input voice recognition is processed at different periods and other factors based on the KB, and the training data prediction instance does not update interaction recognition. The continuous training data is based on multilingual interactions with pitch and tone through applications for preventing communication errors. The computation of the sought-after input speech recognition relies on current and historical data prediction for the various precise content retrieval and their features extraction in the previous knowledge-based. From the interactive input recognition based on the condition $(f \times P_c) > (t \times P_c)$ is evaluated using training data prediction for automatic error correction. A processing system can analyse human interactions based on the precision of content retrieval and the versatility of NLP models. Human voice recognition is the foundation for feature extraction and prediction, which uses a phonetic KB to eliminate misunderstandings in spoken communication. As shown in Figure 12, the proposed method detects mistakes in phonetics analysis during input recognition compared to retrieval times for previously precise content.

4.5 | Error

In Figure 13, the KB updating through different training data predictions is analysed using voice recognition based on a communication error. The identified errors and interactions based on the multilingual NLP models and precise content retrieval provide additional training data prediction for prediction. The current prediction and previous content are verified for their phonetics based on different knowledge transfers. At various points, phonetics observations forecast future training data based on the communication fault found through content-based retrieval. By incorporating data gleaned from a variety of voice recognition programs, this database can be used for both training and multilingual processing. The multilingual training interactions based on the $\frac{\rho_p.\text{Precise content }(n).[(P_c - T_o)Ph_n]}{F(\alpha).N}$ Condition processed sequentially. This distributed transfer learning identifies communication errors due to vast data processing and interaction recognition based on content retrieval precision. The communication errors can be analysed through feature extraction for performing the automatic error correction at the time of prediction. The suggested strategy reduces error by learning from past content-based predictions and applying that information to an updated KB. Tables 1 and 2 show the outcomes of the comparisons made.

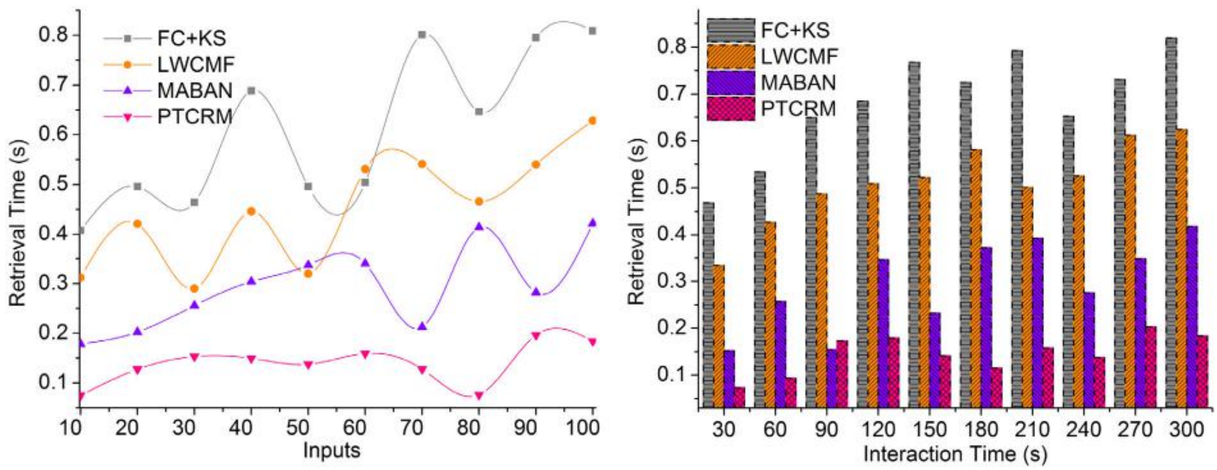

FIGURE 12 Retrieval time comparisons

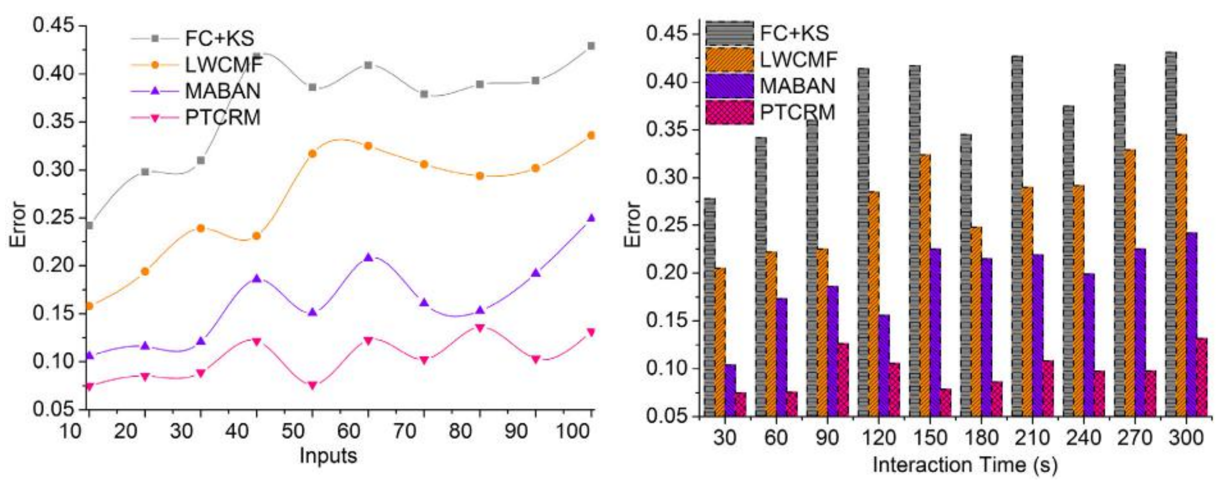

FIGURE 13 Error comparisons

TABLE 1 Comparative analysis results for inputs

Metrics	FC + KS	LWCMF	MABAN	PTCRM	Observations
Prediction precision	0.539	0.691	0.811	0.9181	11.89% High
Retrieval accuracy (%)	50.74	68.31	81.04	90.199	11.75% High
Features	36	66	91	139	8.95% High
Retrieval time (s)	0.809	0.628	0.422	0.1837	11.72% Less
Error	0.429	0.336	0.249	0.1318	10.31% Less

Abbreviations: MABAN, multi-agent boundary-aware network; PTCRM, predictive typological content retrieval method.

TABLE 2 Comparative analysis results for interaction time

Metrics	FC + KS	LWCMF	MABAN	PTCRM	Observations
Prediction precision	0.528	0.672	0.816	0.9263	12.72% High
Retrieval accuracy (%)	51.91	65.39	81.53	90.431	12.08% High
Features	39	71	95	132	8.04% High
Retrieval time (s)	0.819	0.624	0.418	0.1832	11.75% Less
Error	0.431	0.345	0.242	0.1316	10.39% Less

Abbreviations: MABAN, multi-agent boundary-aware network; PTCRM, predictive typological content retrieval method.

5 | CONCLUSION

This article introduced a PTCRM using multilingual NLP. The proposed method identifies the input based on tone and pitch features for phonetics detection. Based on the detected phonetics, the classification for matching and un-matching features is performed. Using the knowledge of transfer learning, the different inputs are trained for error and matching contents. This improves the retrieval precision, providing better support for real-time applications. The knowledge is transferred for validating the recognition instances such that multilingual phonetics is treated unanimously. Based on the prediction probability from distinct training instances, the error is reduced. In the given processing time, the un-matching and matching features are classified and validated for the available phonetics for optimal content retrieval. The successive training and knowledge update instances are used for verifying the tone and pitch-based entity assessment. The experimental analysis shows that the proposed method improves prediction precision by 12.72%, retrieval accuracy by 12.08%, and features by 8.04%; the retrieval time and error are suppressed by 11.75% and 10.39%, respectively, under varying interaction times.

DATA AVAILABILITY STATEMENT

Research data are not shared.

ORCID

S. Baskar https://orcid.org/0000-0003-3570-3059

REFERENCES

Ait-Mlouk, A., & Jiang, L. (2020). KBot: A knowledge graph based chatBot for natural language understanding over linked data. *IEEE Access*, *8*, 149220–149230.

Boros, E., Nguyen, N. K., Lejeune, G., & Doucet, A. (2022). Assessing the impact of OCR noise on multilingual event detection over digitised documents. *International Journal on Digital Libraries*, *23*, 1–26.

Cai, J., Dan, W., & Zhang, X. (2019). ℓ0-based sparse canonical correlation analysis with application to cross-language document retrieval. *Neurocomputing*, *329*, 32–45.

Chen, Z., Cheng, X., Dong, S., Dou, Z., Guo, J., Huang, X., Lan, Y., Li, C., Li, R., Liu, T., Liu, Y., Ma, J., Qin, B., Wang, M., Wen, J., Xu, J., Zhang, M., Zhang, P., & Zhang, Q. (2021). Information retrieval: A view from the Chinese IR community. *Frontiers of Computer Science*, *15*(1), 1–15.

Cui, Y., Zhang, W. N., Che, W., Liu, T., Chen, Z., & Wang, S. (2022). Multilingual multi-aspect explainability analyses on machine reading comprehension models. *iScience*, *25*(5), 104176.

De la Rosa, J., Pérez, Á., De Sisto, M., Hernández, L., Díaz, A., Ros, S., & González-Blanco, E. (2021). Transformers analyzing poetry: Multilingual metrical pattern prediction with transfomer-based language models. *Neural Computing and Applications*, 1–6. https://doi.org/10.1007/s00521-021-06692-2

Edmonds, R. (2020). Multilingualism and the politics of participation at a Cameroonian wildlife sanctuary. *Language & Communication*, *72*, 1–12.

El-Alami, F. Z., El Alaoui, S. O., & Nahnahi, N. E. (2021). A multilingual offensive language detection method based on transfer learning from transformer fine-tuning model. *Journal of King Saud University-Computer and Information Sciences*, *34*(8), 6048–6056.

Enamoto, L., & Weigang, L. (2021). Generic framework for multilingual short text categorization using convolutional neural network. *Multimedia Tools and Applications*, *80*(9), 13475–13490.

Interdonato, R., Guillaume, J. L., & Doucet, A. (2019). A lightweight and multilingual framework for crisis information extraction from Twitter data. *Social Network Analysis and Mining*, *9*(1), 1–20.

Kamper, H., Matusevych, Y., & Goldwater, S. (2021). Improved acoustic word embeddings for zero-resource languages using multilingual transfer. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *29*, 1107–1118.

Kanfoud, M. R., & Bouramoul, A. (2022). SentiCode: A new paradigm for one-time training and global prediction in multilingual sentiment analysis. *Journal of Intelligent Information Systems*, *59*, 1–22.

Li, B., Du, X., & Chen, M. (2020). Cross-language question retrieval with multi-layer representation and layer-wise adversary. *Information Sciences*, *527*, 241–252.

Li, X., Xu, C., Wang, X., Lan, W., Jia, Z., Yang, G., & Xu, J. (2019). COCO-CN for cross-lingual image tagging, captioning, and retrieval. *IEEE Transactions on Multimedia*, *21*(9), 2347–2360.

Litschko, R., Vulić, I., Ponzetto, S. P., & Glavaš, G. (2022). On cross-lingual retrieval with multilingual text encoders. *Information Retrieval Journal*, *25*(2), 149–183.

Ma, Y., Xie, Z., Li, G., Ma, K., Huang, Z., Qiu, Q., & Liu, H. (2022). Text visualization for geological hazard documents via text mining and natural language processing. *Earth Science Informatics*, *15*(1), 439–454.

Meesad, P. (2021). Thai fake news detection based on information retrieval, natural language processing and machine learning. *SN Computer Science*, *2*(6), 1–17.

Nishimura, Y., Sudoh, K., Neubig, G., & Nakamura, S. (2019). Multi-source neural machine translation with missing data. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *28*, 569–580.

Pająk, K., & Pająk, D. (2022). Multilingual fine-tuning for grammatical error correction. *Expert Systems with Applications*, *200*, 116948.

Qiu, X., Sun, T., Xu, Y., Shao, Y., Dai, N., & Huang, X. (2020). Pre-trained models for natural language processing: A survey. *Science China Technological Sciences*, *63*(10), 1872–1897.

Roostaee, M., Sadreddini, M. H., & Fakhrahmad, S. M. (2020). An effective approach to candidate retrieval for cross-language plagiarism detection: A fusion of conceptual and keyword-based schemes. *Information Processing & Management*, *57*(2), 102150.

Shiah, C. Y. (2020). Content-based document image retrieval based on document modeling. *Journal of Intelligent Information Systems*, *55*(2), 287–306.

Solainayagi, P., & Ponnusamy, R. (2019). Trustworthy media news content retrieval from web using truth content discovery algorithm. *Cognitive Systems Research*, *56*, 26–35.

Sun, X., Wang, H., & He, B. (2021). MABAN: Multi-agent boundary-aware network for natural language moment retrieval. *IEEE Transactions on Image Processing*, *30*, 5589–5599.

Wajsbürt, P., Sarfati, A., & Tannier, X. (2021). Medical concept normalization in French using multilingual terminologies and contextual embeddings. *Journal of Biomedical Informatics*, *114*, 103684.

Wang, Q., Zhang, J., & Zong, C. (2022). Synchronous inference for multilingual neural machine translation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *30*, 1827–1839.

Wang, Y., & Zhang, C. (2020). Using the full-text content of academic articles to identify and evaluate algorithm entities in the domain of natural language processing. *Journal of Informetrics*, *14*(4), 101091.

Ye, Q. (2021). Situational English language information intelligent retrieval algorithm based on wireless sensor network. *International Journal of Wireless Information Networks*, *28*(3), 287–296.

Yusuf, B., Gundogdu, B., & Saraclar, M. (2019). Low resource keyword search with synthesized crosslingual exemplars. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *27*(7), 1126–1135.

AUTHOR BIOGRAPHIES

S. Baskar, assistant professor in the Department of Electronics and Communication Engineering/Center for Interdisciplinary Research, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India. He worked as a research associate in the Departments of Nano Science and Technology and Pervasive Computing Technology. His research interests include wireless sensor networks, low power VLSI, IoT, material science. He published more than 33 research articles in international journals, book chapters, and conferences. So far, he guided 20 ME/MTech/BE projects. He is a reviewer for referred journals like *Wireless Sensor Networks*, *IEEE Access*, *Inderscience* and *IEEE Transactions on Vehicular Technology*. He is a Young Scientist Awardee by the Department of Science and Technology, Government of India.

Sunita N. Dhote, assistant professor in the Department of Management Technology, Shri Ramdeobaba College of Engineering and Management, Nagpur, Maharashtra, India. She is chairperson of Women Empowerment Cell of the college. Her research interests include entrepreneurship, finance and women empowerment. He published more than five research articles in international journals, and conferences. She has written a book on Marketing Management. She is an Asia Book of Record Holder for Longest Distance Cycling. She holds a Guinness Book of Records in 'The most people in a single mountain run at Satara Hill Half Marathon at Satara, Maharashtra, India, on 17 September'.

Tejas N. Dhote is a master's student at the Department of Mechanical Engineering—Engineering Mechanics, Michigan Technological University, Michigan, United States. He is focusing on Automotive Powertrains and Controls Engineering in his master's and has done more than 10 projects related to them. He has also done his bachelor's from Shri Ramdeobaba College of Engineering and Management, where he has published a paper on Worker health monitoring systems. He holds a Guinness Book of Records in 'The most people in a single mountain run at Satara Hill Half Marathon at Satara, Maharashtra, India, on 17 September'.

G. Jayanandini, assistant professor in the Faculty of Architecture, Design and Planning, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India. Her focus areas involve urban planning, urban design and housing. During her tenure at the university, she has published four research papers in international journals and conferences and was engaged in development plans, such as preparing master plans for Coimbatore and Tiruppur cities. She has a Master's in Architecture degree in Habitat Design from BMS College of Engineering and Technology, Bangalore and under graduate in BArch from Karpagam Academy of Higher Education, Coimbatore.

D. Akila completed her post-doctoral fellow in Computer Science, Lincoln University College, Malaysia and PhD, in Computer Science from Bharathiar University, Tamil Nadu, India. She received his MCA from Bharathiar University, MPhil, degree from Bharathidasan University, ME, Computer Science and Engineering from Vinayaka Mission University. She is currently working as professor, Department of Computer Applications, Saveetha College of Liberal Arts and Sciences, SIMATS Deemed University, Chennai, Tamil Nadu, India which is well known University. Her research interests include data mining, big data analytics, cloud computing, image processing, knowledge-based systems and web information exploration. She has published more than 75 research papers in various International Journal such in Scopus, Springer and UGC referred journals. She has authored six books.

Srinath Doss received his PhD in Computer Science and Engineering from St Peter's University in 2014, Master of Engineering degree in Computer Science and Engineering in 2006 from Anna University and Bachelor of Technology in Information Technology in 2004 from the University of Madras. He is currently a fellow with the Faculty of Computing, Botho University, Gaborone, Botswana. Previously, he worked at various colleges in India and Garyounis University, Libya. He has published and presented more than 16 papers in international journals and six prestigious conferences. His research interests include network security and cryptography, cloud computing, wireless and sensor network, and mobile computing. He serves as the reviewer for seven international journals and advisor for the Research Scientific Publishing Development Organization. He has been session chair and advisory member for various international conferences. He is also a member of the Computer Society of India.

How to cite this article: Baskar, S., Dhote, S., Dhote, T., Jayanandini, G., Akila, D., & Doss, S. (2022). A predictive typological content retrieval method for real-time applications using multilingual natural language processing. *Expert Systems*, e13172. https://doi.org/10.1111/exsy.13172