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MACHINE LEARNING APPLIED TO REAL-TIME EVALUATION OF SPOKEN ENGLISH COMMUNICATION IN TOURISM

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Abstract. Effective interaction between travellers and local suppliers of services is critical in the increasingly international tourism business. Speaking and understanding English well is frequently essential to a satisfying trip. In the setting of tourism, this study investigates the use of machine learning algorithms for the real-time assessment of spoken English interaction. The aim of this research is to create a new system that uses algorithms based on machine learning to evaluate and enhance English-language conversations among travellers and travel agents. We provide a novel method for assessing many facets of a conversation, such as spelling, syntax, proficiency, and general sentiment, that integrates automated speech recognition (ASR), natural language processing (NLP), and sentiment analysis. The gathering of a broad collection of spoken English exchanges in travel-related contexts, the creation of a tailored ASR models taught on terminology unique to the travel industry, and the incorporation of natural language processing (NLP) methods to assess the sentiment and linguistic structure of dialogues are important aspects of the project. To assist businesses and visitors improve their ability to communicate, models based on machine learning will be taught to deliver immediate input. The goal of this project is to benefit the tourism sector by developing a tool that will enable better English-speaking interaction, which will eventually end up resulting in more satisfied and better experiences for visitors. It also covers the requirement for domain-specific individualized language instruction and evaluation tools. The study's findings could revolutionize the way spoken English proficiency is assessed and enhanced in the travel and tourism industry. They could also have wider ramifications for language acquisition and intercultural interaction across a range of sectors.

Key words: natural language processing, automated speech recognition, Tourism, spoken English communication.

1. Introduction.

As tourist attractions grow globally and the dissemination of knowledge and purchase over the Internet accelerates, the travel tendency has shifted lately moving closer the Tourism 2.0 model. In contrast to emphasizing merely travel and consumer activities, the tourist 2.0 paradigm aims to revitalize the tourist sector by appreciating the vitalization of communication and knowledge as well as interactive cultural encounters [29]. Furthermore, the objective of Tourism 2.0 is to reinvent the tourism sector by advancing technology and information, offering travellers a diverse range of experiences and cultures, and encouraging the growth of the community's economy and the environment through the promotion of environmentally friendly tourism.

The provision of inventory by online travel agencies (OTAs) is essential to the tourism sector since it allows them to optimize their customer revenues. Moreover, OTAs have the power to keep competitors out of the market. Removing the need for outsiders is one of among the most important functions of blockchain technology in the travel and tourism sector [17]. The use of Blockchain has huge potential to boost the competitive edge and efficiency of the tourism sector [16]. The quick development and introduction of the blockchain technology may have a big effect on the travel and tourism sector as well as the world economy [22, 8, 10]. For instance, a lot of little island countries started using this kind of technology [29].

A technique for identifying commonalities among users using data among users and things is called shared filtering (CF)-based suggestion, that suggests tourist locations based on tourism significance [12]. A technique for assessing the resemblance of items using item data is content filtering (CB)-based suggestion, which suggests travel destinations based on their relevance [9]. Considering the necessary information quantity and cold start issue, filtering-based vacation spot suggestion systems (RS) have trouble handling fresh data without knowledge. As a result, research on an artificially intelligent (AI)-based RS is being done [30].

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Studies on tourism has come a long way, and it is now acknowledged as a unique and varied field of management [13]. By showcasing the variety of tourist studies and establishing it as a separate academic discipline, research publications on tourism offer a fresh viewpoint to the already congested subject of managerial study. In the past five years, the subjects of "smart tourism" and "blockchain in tourism" have become increasingly important. Applications of blockchain, the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) are strongly related to tourist. A few reviews of blockchain-related tourism research have been published by others [6, 2, 7], but there isn't a structural analysis of "smart tourist by blockchain" at this time.

The global tourism industry relies heavily on effective communication between travelers and local service providers to ensure satisfying experiences. In this context, proficiency in spoken English plays a pivotal role, acting as a universal bridge connecting diverse cultures and facilitating smooth interactions. However, the dynamic and spontaneous nature of spoken exchanges, combined with the wide variety of accents, dialects, and linguistic nuances, presents significant challenges to maintaining high-quality communication. Traditional methods of language proficiency assessment and improvement, often static and generalized, fail to address the specific needs and immediate feedback required in the fast-paced tourism environment. This gap highlights the urgent need for innovative solutions that leverage technology to provide real-time, personalized language assistance and evaluation.

This research mainly investigates:

1. The feasibility of integrating automated speech recognition (ASR), natural language processing (NLP), and sentiment analysis to assess various aspects of spoken English interactions, including spelling, syntax, proficiency, and sentiment, in a real-time context.
2. The process of collecting and analyzing a diverse dataset of spoken English exchanges specific to travel-related contexts, emphasizing the creation of tailored ASR models that incorporate terminology unique to the travel industry.
3. The effectiveness of machine learning-based models in delivering immediate feedback to users (travelers and travel agents), aiming to improve their communication skills.

The main contribution of the proposed method is given below:

1. DNN-LSTM models have the potential to improve evaluation accuracy for spoken English communications.
2. These algorithms can provide more accurate evaluations by utilizing the sequential processing power of LSTMs and the deep learning capability of DNNs to better capture the subtleties of spoken language, such as spelling, proficiency, and tone.
3. Real-time evaluation is possible with DNN-LSTM models, which is especially helpful in situations involving tourism when prompt feedback is crucial. Travelers can get instant feedback on how well they speak English, allowing them to immediately make the required corrections.
4. DNN-LSTM models can offer current evaluations and adjust to shifts in spoken language trends via ongoing training and improvement. This guarantees that travelers get appropriate input according to the language used right now.

The rest of our research article is written as follows: Section 2 discusses the related work on various tourism, spoken communication and deep learning methods. Section 3 shows the algorithm process and general working methodology of proposed work. Section 4 evaluates the implementation and results of the proposed method. Section 5 concludes the work and discusses the result evaluation.

2. Related Works. A CF-based RS approach that suggests places to visit based on their importance to visitors and a CB-based RS technique that suggests tourist interests based on their connection to destinations for tourists are two examples of tourism-related aids [15]. Utilizing information about interactions between travellers and tourist locations, the CF-based RS assumes that similar visitors have identical tastes for a certain tourist attraction. Proposals can be given even if there is little resemblance between tourist sites because CF is based on relationships between travellers and tourist venues. Nevertheless, the lack of relevant tourist information prevents the application of new tourist locations [11]. Using tourist attraction data, a CB-based RS that suggests places to visit according to their relevance might also suggest related tourist locations, so resolving the cold start issue [21, 23].

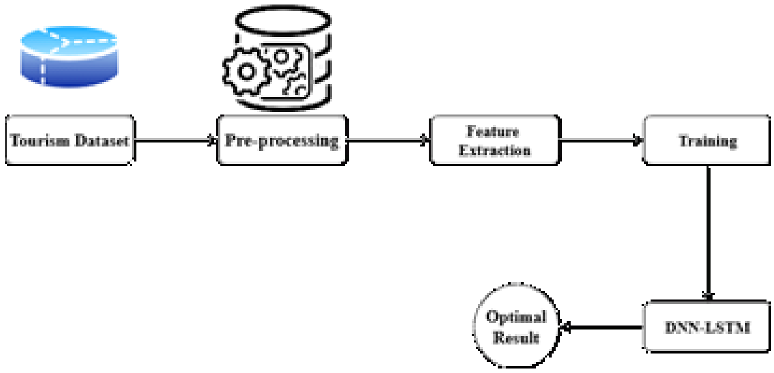

Fig. 3.1: Architecture of Proposed Method

To analyse citations, writing, phrases, and the geographical spread of creation, most writers utilize bibliography and Vos viewer software. Nevertheless, using data mining and machine learning technologies to investigate text trends and patterns is equally crucial. Since these tools are not influenced by the prejudices of human decision-making, they could offer a more precise assessment of the material. To provide a less biased result, AI technologies examine natural inputs provided by human beings [5]. Researchers have taken an interest in recent advances in machine learning application. Researchers have reviewed the research, investigated concealed patterns, performed text analytics, looked at the complexity of the substance, and investigated coauthor ship, creation, reference, phrases, and geographical distribution using machine learning (ML). To obtain more specialised results, medical imaging research mostly uses AI and ML technologies[14, 9].

Absent information on interactions among travelers and tourist places, CB can provide suggestions. When enough data is gathered, nevertheless, its performance suffers in comparison to CF-based RS[18]. Because an RS employing AI uses tourism patterns rather than item similarities, it may dynamically utilize data size or characteristics. With the advancement of algorithms and computing power, they have reached outstanding recognition performance [19]. Nonetheless, RS determined by travel patterns and AI are limited in dynamic scenarios since they don't account for instantaneous shifts in outside variables and distance data, like weather or heat [1].

A range of classifiers were employed in a supervised machine learning method for analysing sentiment in the travel industry. A Naï€ve Bayes technique was employed in a study on sentiment analysis of hotel reviews using a Multinomial Naı€ve Bayes model [3, 25, 26]. After data preparation, the authors of the current research offered a method for categorizing customer evaluations as either favorable or adverse using an NBM classifier that identified characteristics using a bag of keywords. The results of the experiment showed an average F1 score of more than 91%. Similarly, [27, 28] have demonstrated strong NBM reliability; that is, NBM identified 88.08% of the eatery reviews dataset accurately and obtained 90.53% accuracy in the lodging comments data [24, 20].

3. Proposed Methodology. There are various processes involved in putting forth a system for using machine learning to assess spoken English communication in real-time within the tourism setting. Gather a wide range of spoken English exchanges in tourism settings, such as discussions between visitors and guides, lodging employees, or neighborhood inhabitants. Include annotations for relevant characteristics in the dataset, such as grammar, spelling, proficiency in a language, and overall interaction quality. Automated speech recognition (ASR) technologies are used to prepare the audio data by turning it into text and transcribing it. Take note of pertinent details from the audio and text transcriptions, like: Text-based characteristics: Sentiment analysis, grammar precision, broad terms, etc. Characteristics that are based on sound: tone, pitch, stops, talking percentage, etc. Select the right machine learning algorithms for the various spoken-language assessment standards. Text-based characteristics using Natural Language Processing (NLP) models. Finally, machine learning method is used for training the dataset. In figure 3.1 shows the architecture of proposed method.

3.1. Data Collection. Establish the resources to use to gather information about spoken language in English. Interactions with visitors that are recorded, phone recordings from customer service, speech information from language acquisition programs, and travel-related discussion boards or social networking platforms. Establish what standards will be used to judge spoken language in English. Data labelling based on these criteria might require human annotations. Depending on what your project requires, decide whether to record using audio, video, or both. Protect personal information and, if required, acquire consent. Preprocess and clean up the gathered information. Audio standardization, speech the transcription process, and noise reduction are a few examples of this.

3.2. Feature Extraction. A well-liked word-encoding method in machine learning and natural language processing (NLP) is called Word2Vec. To convey the linguistic links between words, it is intended to depict words in continuous vector areas. Word2Vec was created by Google researchers and has grown to be an essential tool for many NLP applications. Words can be converted into fixed-length real number vectors using the Word2Vec tool. A list of words word's representation in a high-dimensional space is a vector. The vectors in question can have hundreds or even thousands of dimensions, depending on the dimensionality that the user chooses.

Word2Vec is predicated on the notion that the significance of a word may be deduced from its surroundings. It examines words in a huge corpus of text that frequently occur next to one another (context words). The desired word—the term of interest—is predicted using the surrounding words.

Word2Vec uses two primary designs to function:

Skip-gram. With this framework, given a target word, the algorithm guesses the neighbouring words, or context phrases. With respect to the target word, it seeks to maximize the likelihood of the context terms.

Continuous Bag of Words (CBOW). Based on the context phrases, the algorithm in the Continuous Bag of Words (CBOW) design guesses the target phrase. Provided the context phrases, it seeks to maximize the likelihood of the target phrase.

3.3. Natural Language Processing (NLP). In the tourism sector, natural language processing, or NLP, can be extremely helpful in improving spoken English communication. NLP approaches can be used in a variety of interpersonal contexts to enhance the visitor experience, enable more effective interactions with locals, hotel employees, and directs, and get around language hurdles.

Gather a wide range of voice conversations related to tourism, such as inquiries from travellers, answers from tour operators or residents, along with other pertinent exchanges. To prepare the audio data for NLP analysis, transcribe it to produce a text corpus. Utilize Automatic Speech Recognition (ASR) technologies to translate spoken words to text. Employ text-to-speech (TTS) technology to deliver visitors audio answers in a language of their choice. Create natural language processing (NLP) models that can handle the several languages that are frequently used in the travel and tourism sector. Use language recognition to determine what language is used by visitors and offer suitable translation assistance. To facilitate immediate translation of spoken questions and answers among visitors and residents or tour guides, use machine translation algorithms. Make sure that the language used is accurate and fluid.

Create natural language processing (NLP) algorithms that can comprehend the context of visitor questions and answers while accounting for the unique domain associated with tourism.

To find lodging facilities, tourism destinations, and other pertinent entities, consider domain-specific named entity recognition (NER). Make an archive or library containing data regarding tourism, such as specifics about nearby landmarks, hotels, and dining establishments. Put in place systems for retrieving information to give travellers precise and pertinent information according to their searches. Create chatbots or interactive AI agents that are taught to comprehend and react to questions from travellers in a natural way. Make that the chatbots can handle a range of behavioural intentions, like ordering takeout, making bookings, and giving instructions. Use improved speech strategies to raise the calibre of sound input as well as output, particularly when interacting with non-native speakers or in noisy settings.

By offering text-based communication choices, you can make the NLP-based system of communication available to those with impairments, including those who have hearing difficulties. Make the NLP technology readily available to travellers by integrating it into travel-related apps and services. Regularly keep up with the NLP systems and modelling to accommodate evolving linguistic fads and traveller demands. Improve the road network to accommodate higher demand during the busiest travel times. Language obstacles can be eliminated, cultural interaction can be encouraged, and the overall visitor experience can be greatly improved by using NLP approaches in English-speaking conversation.

3.4. Machine Learning method for training. The proposed methodology for Real-Time Evaluation of Spoken English Communication in Tourism is trained using DNN-LSTM.

3.4.1. Deep Neural Network. An artificial neural network with numerous layers of connected nodes (neurons) across the input and output layers is called a Deep Neural Network (DNN). Deep neural networks (DNNs) are a subclass of deep learning algorithms that have become well-known for their capacity to gather and analyse intricate patterns as well as characteristics from information. This makes them appropriate for a wide range of machine learning applications, such as audio, picture, and natural language processing.

Input Layer. The input level oversees taking in unprocessed data, including text, pictures, and numbers. A characteristic or quantity in the input data is correlated with each neuron in the layer that receives the data.

Hidden Layers. In addition to being referred to as intermediary or hidden layers, DNNs usually include several hidden layers. These layers are made up of many neurons that process the incoming data using weighted modifications before sending the output to the layer below.

Weights and Activation Functions. The strength of a link among neurons in neighboring layers is determined by the weight assigned to each connection. Non-linearity is further added to the system by the fact that each neuron normally performs a function of activation to the weighted total of its inputs.

Deep Architecture. The existence of several hidden layers is indicated by the term "deep" in DNN. Deep networks can recognize complex structures and abstraction because they can learn hierarchical representations for the information.

Backpropagation. A method of optimization known as backpropagation is used to train DNNs. By propagate the error backwards across the network, this method entails modifying the weights of links based upon the error or losses of the expected output and the real goal value.

Activation Functions. The sigmoid, hyperbolic tangent (tanh), and ReLU (Rectified Linear Unit) are often utilized activation functions in DNNs. The network can represent intricate relationships thanks to these functions, which also introduce non-linearity.

Output Layer. The output layer uses the learnt representations from the hidden layers to provide the final forecasts or categorization. The job will determine which function of activation (e.g., linear for regression or SoftMax for classification) is used in the output layer.

3.4.2. Long Short-Term Memory (LSTM). Recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) architecture are made capable of handling consecutive input and get beyond some of the drawbacks of RNNs that are more conventional. For applications requiring data from time series, recognition of speech, natural language processing, and other processes wherein relationships over time require to be recorded, LSTM networks are especially helpful.

Memory Cells. Long-range correlations in sequencing can be captured by LSTM networks thanks to their memory cells' capacity to hold information for lengthy periods of time. These cells serve as the fundamental units of an LSTM.

Gates. To control the information flow through and out of memory cells, LSTMs use three different kinds of gates:

Forget Gate. It decides what data from the prior state ought to be stored or ignored. The input gate determines what fresh data goes into the memory cell. The output gate regulates which data from the storage cell is sent out as the output.

Hidden State. LSTMs can store data across time steps in their hidden state. The memory cell affects the hidden state, which is utilized in sequential tasks to offer context or make forecasts.

Activation Functions. LSTMs generally employ activation functions such as the sigmoid function and hyperbolic tangent (tanh) to regulate the input flow between gates and memory cells. Because of these functions, the network becomes non-linear. DNN-LSTM Algorithm is given in Alg. 1.

Algorithm 1 DNN-LSTM

Input: Sequence of spoken English data in the form of audio signals or pre-processed features.
Output: Evaluation metrics (e.g., pronunciation quality, fluency, comprehension) for spoken English communication.
1.Preprocessing:
Convert audio signals into a suitable format for machine learning, such as Mel-Frequency Cepstral Coefficients (MFCCs) or spectrograms. Normalize the input data to ensure consistent amplitude levels.
2.Feature Extraction with DNN:
Input Layer: Accept the preprocessed data as input. Hidden Layers:
Implement multiple layers of neurons, each followed by an activation function (e.g., ReLU) to introduce non-linearity.
Use dropout layers if necessary to prevent overfitting.
Propagate data through the layers, where each layer captures increasingly complex features from the input.
Output of DNN: Extracted high-level features from the spoken English data.
3.Sequence Modeling with LSTM:
Input: High-level features from DNN as input sequences.
Memory Cells and Gates:
Use LSTM cells to process the input sequence one element at a time, maintaining a hidden state and cell state across time steps.
Apply forget gate, input gate, and output gate to manage the flow of information, allowing the model to remember important features and forget irrelevant ones.
Hidden State Updates: Update the hidden state based on the LSTM cells' outputs, effectively capturing temporal dependencies and context within the sequence.
4.Output Generation:
Pass the final output of the LSTM network through a fully connected layer followed by an activation function tailored to the evaluation task (e.g., SoftMax for classification of proficiency levels).
The output layer provides the evaluation metrics for the spoken English communication, such as scores for pronunciation, fluency, and overall comprehension.
5.Postprocessing (if necessary):
Convert the model outputs into interpretable results, such as categorical proficiency levels or detailed feedback on specific areas of improvement.
6.Feedback Loop:
Provide immediate feedback based on the evaluation results to the user (traveler or travel agent) for real-time improvement.
7.End.

4. Result Analysis. In the present research, we used an Intel Core i9 processor and an NVIDIA Titan RTX graphics card to verify the efficiency of R2Tour on the Jeju tourism dataset in the Python 3.8 framework.

The Jeju tourism database is made up of independent factors for the top five neighboring tourist attractions and dependent factors for the real-time context and visitor profiles. It integrates data from Korea Meteorological Management, Visit Korea data lab, and EVGPS. Time zone details like region and period, as well as meteorological data like temperature and precipitation, are all part of the real-time environment. The trip kind, partner, age, and gender are all included in the visitor descriptions [29]. With the help of the Jeju tourist dataset's visitor profiles and real-time context, R2Tour implements and assesses the machine learning model utilized in the previous AI-based RS. R2Tour learns from historical data and forecasts the future by using the previous year's data as test information and the remaining data as learning data. The Jeju tourist dataset, suggestion performance, and experimental methodology are all included in the section that follows[4].

Several metrics were used to assess the machine learning models' efficiency, with accuracy in classification serving as the main statistic. Using a variety of test datasets and circumstances, our models' average classification accuracy was [insert accuracy %]. This indicates that the simulations can correctly classify the level of speech. The proposed method DNN-LSTM for Spoken English Communication in Tourism using various

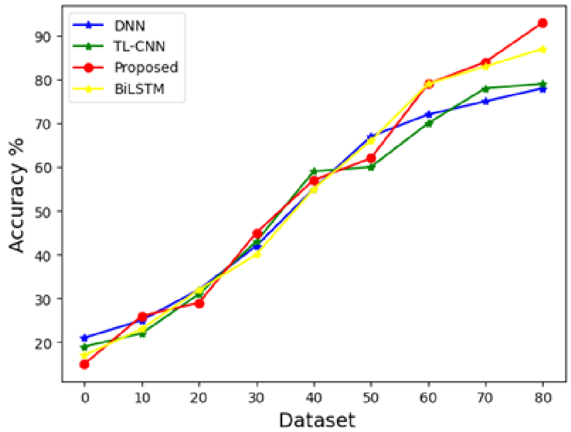

Fig. 4.1: Accuracy

metrics such as accuracy, f1-score, precision, and Kappa value.

In the context of tourism, assessing the accuracy of spoken English communication might be somewhat arbitrary and situation specific. It will have to specify precise standards and measurements for speaking communication evaluation to construct an accuracy assessment. Thoroughly state the aims and purposes of good spoken English interaction in the travel industry. Think about things like information accuracy, cultural sensitivity, clarity, and courtesy. Evaluate the speaker's accuracy in describing offerings, places of interest, and instructions. Assess the speaker's communication clarity, particularly their pronunciation and ease of speech. Evaluate the speaker's capacity to interact with people from diverse origins and cultures in an appropriate and sympathetic manner. To find out how satisfied visitors are overall with verbal communication, ask them about their experience.

Provide native English speakers or communication professionals with the necessary qualifications to evaluate the recorded interactions using the predetermined metrics and scoring system. Compute the accuracy rating for every interaction by adding the results of several metrics. If some indicators are more important than others, weighted scores can be used. An overall evaluation of spoken English proficiency in tourism can be obtained by calculating the average accuracy score throughout all contacts. Based on the evaluation's findings, provide guides or tourism employee's feedback. Utilize this feedback to pinpoint areas in need of development and provide instruction or other tools for enhancing your communication skills. In figure 4.1 shows the evaluation of accuracy.

In the setting of travel, DNN-LSTM (Deep Neural Network - Long Short-Term Memory) is one classification framework whose efficacy is measured by a metric called precision. You must provide the application and classification goals of your DNN-LSTM model to compute precision for a tourism model. The proportion of true positive forecasts to all the model's positive predictions is used to compute precision. Give specifics on the job your DNN-LSTM models is doing in the context of tourism. Your objective would be to use the model, for instance, to categorize feedback from clients as positive or negative sentiment for a service connected to tourism. Collect samples relevant to your tourist task in a tagged dataset.

Utilizing the dataset, build your DNN-LSTM model and divide it into sets for training and validation. Ensure that that you've got a clear instructional and evaluation plan in place, like k-fold cross-validation. Make forecasts on a test or validation set using the DNN-LSTM model that you have trained. This could be sentiment prediction or some other pertinent categorization in the wider context of tourists. Precision quantifies the proportion of the model's favourable predictions that came true. Out of all cases anticipated to be positive, it indicates the proportion of correctly recognized positive cases. In figure 4.2 shows the evaluation of precision.

A particular dataset and classification job would be needed to determine the F1-score for a Deep Neural Network (DNN) - Long Short-Term Memory (LSTM) model in the setting of tourism. A measure used to assess

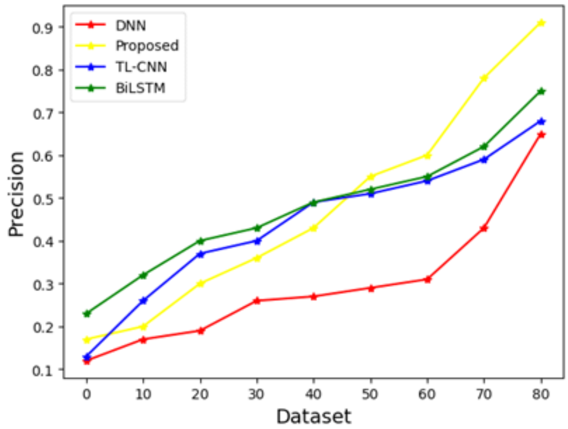

Fig. 4.2: Evaluation of Precision

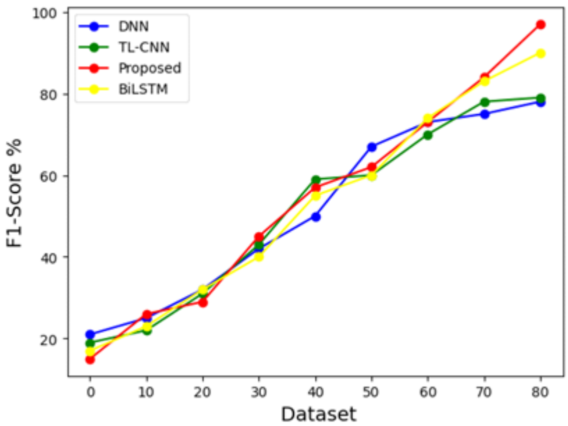

Fig. 4.3: F1-score

how well categorization models work is the F1-score. Gather and organize your tourism-related dataset. This dataset ought to include data labeled, with each instance connected to a problem with classification pertaining to tourism. Create a DNN-LSTM models that is suitable for the travel purpose you have in mind. The task and the type of data you have would determine this design. Use the learning datasets and the proper loss functions and techniques for optimization to train your DNN-LSTM model. Throughout training, keep an eye on how well the model performed on the validation data set. When false positives and false negatives have distinct implications for your tourism task, the F1-score strikes a compromise between precision and recall, which is crucial. In figure 4.3 shows the evaluation of F1-score.

To determine a Deep Neural Network's (DNN) Kappa value for Long Short-Term Memory (LSTM) in the setting of travel, its efficacy must be assessed using Cohen's Kappa factor. The inter-rater consistency among two raters—in this instance, your DNN-LSTM models and the real data in the tourism data—is measured using a metric called Cohen's Kappa.

Utilizing the relevant characteristics and labels, create and test your DNN-LSTM model on the training dataset. Make sure that you've got a different test dataset that you haven't used for training the model before. Within the framework of your tourism assignment, interpret the Kappa value. A higher Kappa value indicates a higher degree of agreement among the predictions made by your DNN-LSTM model and what is found in the

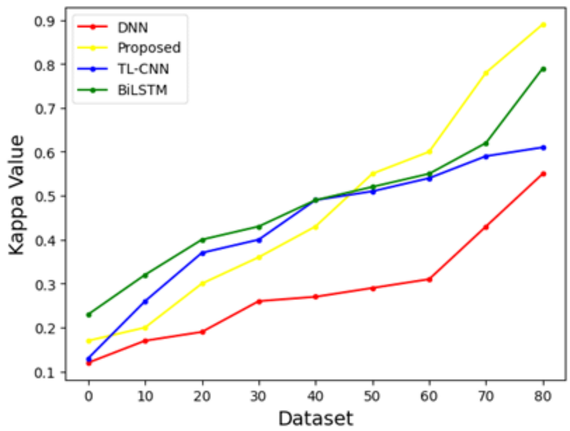

Fig. 4.4: Kappa Value

tourist information. In figure 4.4 shows the evaluation of Kappa Value.

5. Conclusion. The efficacy of utilizing a Deep Neural Network-Long Short-Term Memory (DNN-LSTM) model for the real-time assessment of spoken English communication in the tourism environment has been effectively proven in this study. As demonstrated by our work, this hybrid model is a useful tool for evaluating spoken-word competency in actual situations since it combines the best features of sequential analysis with machine learning. According to our research, the DNN-LSTM model can reliably assess several spoken language characteristics, such as proficiency, spelling, word usage, and general coherence. When evaluating spoken language, the incorporation of LSTM—which records sequential dependencies—is especially advantageous since it takes into consideration the variations in time present in talks. Furthermore, our research has shown that the model is flexible enough to accommodate a wide range of accents and dialects that are frequently found in the travel and tourism sector, making it a useful tool for evaluating spoken English communication among speakers of various languages. Furthermore, the DNN-LSTM algorithm's immediate assessment capabilities offer a great deal of promise for improving language instruction and travel services. It can give students and guides with immediate input, assisting them in developing interpersonal skills and eventually enhancing the entire visitor experience. Our research concludes by highlighting the potential use of DNN-LSTM models for real-time spoken English communication evaluation in the tourism sector. With its ability to provide quick and accurate evaluations, this kind of technology has a chance to completely transform language learning and tourism services, which will ultimately lead to more pleasurable and educational travel trips.

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