International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6s
DOI: https://doi.org/10.17762/ijritcc.v11i6s.6825
***Article Received**: 20 March 2023 **Revised**: 24 April 2023 **Accepted**: 25 May 2023*

Adapting Machine Learning Techniques for Developing Automatic Q&A Interaction Module for Translation Robots based on NLP

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Abstract: Research on Automatic Q&A Interaction Module of Computer-based Translation Robot is a study that focuses on developing an automatic question and answer (Q&A) interaction module for computer-based translation robots. The goal of the research is to enhance the capability of translation robots to perform more human-like interactions with users, particularly in terms of providing more efficient and accurate translations. In this paper proposed a Conditional Random Field Discriminative Analysis (CRFDA) for feature extraction to derive translation robot with Q&A. The proposed CRFDA model comprises of the discriminative analysis for the CRF model. The estimation CRF model uses the bi-directional classifier for the estimation of the feature vector. Finally, the classification is performed with the voting-based classification model for feature extraction. The performance of the CRFDA model is examined based on the Name Entity (Nes) in the TempVal1 &2 dataset. The extraction is based on the strict and relaxed feature model for the exact match and slight variation. The simulation analysis expressed that proposed CRFDA model achieves a classification accuracy of 91% which is significantly higher than the state-of-art techniques.

Keywords: Automatic Q&A Interaction Module, Computer-based Translation Robot, Machine Learning, Part-of-Speech Tagging, Optimal Gradient Descent, Feature Classification.

I. Introduction

The research on Automatic Q&A Interaction Module of Computer-based Translation Robot is an innovative study that aims to improve the ability of translation robots to interact with users by providing more accurate and efficient translations [1 – 5]. To provide the translation robot the ability to understand user questions and respond appropriately, the study employs natural language processing techniques and machine learning algorithms. This research is crucial in addressing the limitations of traditional rule-based methods in translation, which are often inflexible, non-adaptive, and not scalable [6].

The study on Automatic Q&A Interaction Module of Computer-based Translation Robot focuses on enhancing the capability of translation robots to perform human-like interactions with users [7]. The development of an autonomous question-and-answer interaction module is one of the primary goals of this work. Such a module will make it possible for translation robots to comprehend and react to queries posed by users in a manner that is both expedient and correct [8]. This module performs an analysis of the queries posed by users and provides replies that are suitable by using various natural language processing methods and machine learning algorithms [9].

The use of NLP techniques in this study is crucial in enabling the translation robot to understand the meaning and context of users' questions [10]. These techniques involve the analysis of the syntactic, semantic, and pragmatic aspects of language, which are essential in providing accurate translations [11]. The translation robot in this research is able to enhance its performance over time by utilizing machine learning techniques. Training data is utilized to teach the model and fine-tune its settings in order to achieve this goal. Part-of-speech tagging is an important aspect of the proposed Q&A interaction module [12 – 16]. It involves the identification of the parts of speech in a sentence, such as nouns, verbs, adjectives, and adverbs, among others [17 – 19]. This information is used to estimate the grammatical structure of the sentence, which is essential in providing accurate translations. By analyzing the structure of the sentence, the translation robot can determine the relationship between different parts of the sentence and provide appropriate responses to users' questions.

The proposed Optimal gradient descent model is also an important feature of the Q&A interaction module. This model is used to classify the features in the Q&A, which enables the translation robot to identify relevant information in the question and provide accurate responses. The gradient descent algorithm is an iterative optimisation process that is used in machine learning to minimise the loss function. The model employs this approach to achieve its goals.

II. Related Works

In [20] a method based on deep learning was suggested for the purpose of question answering in the context of machine translation. The proposed technique used a convolutional neural network (CNN) to model phrases and a recurrent neural network (RNN) to provide answers to queries. The model was educated using a large collection of parallel texts, and it was tested using two different datasets, namely SQuAD and the Stanford Question Answering Dataset. The findings demonstrated that the suggested technique performed better than the baseline approaches, which included a rule-based approach and a neural machine translation system, among others.

In [21] proposed a multilingual question-answering system for knowledge-based machine translation. The proposed system utilized a knowledge base and a rule-based approach for question answering. The system was designed to handle multiple languages, and was evaluated on a test set consisting of questions and answers in English, French, and German. Based on the findings, it was determined that the suggested system performed well when asked questions on the interpretation of technical words.

In [22] proposed an approach for improving machine translation quality by using automatic question answering. The proposed approach utilized a neural machine translation system and a question-answering model to generate more accurate translations. The model was tested on the WMT14 French-to-English and German-to-English translation tasks, and it was trained using a huge parallel corpus. The outcomes demonstrated the efficiency of the proposed method in enhancing machine translation precision.

In [23] proposed a dual-task generation approach for machine translation and question answering. The proposed approach utilized a sequence-to-sequence model and a reinforcement learning algorithm to generate more accurate translations and answers to user questions. The datasets used for training and testing the model were the WMT14 English-to-French translation challenge and a question-answering dataset with a huge amount of parallel texts. The outcomes validated the efficiency of the proposed method in enhancing the precision of machine translation and question answering.

In [24] combined a rule-based approach with a machine learning-based approach to create a hybrid method for answering multilingual questions using machine translation. the suggested method combines the two methods. For the purpose of question answering, the suggested method made use of a knowledge base as well as a deep learning model. This method was assessed using a dataset that had questions and answers written in both English and Bengali. The findings demonstrated that the strategy that was presented was successful in providing responses to inquiries about machine translation.

In [25] proposed an approach for automatically generating questions for interactive machine translation, which could be used to facilitate more human-like interactions between users and translation robots. The proposed method generated questions from the input text using a sequence-to-sequence model and a reinforcement learning technique. The model was evaluated on a dataset consisting of English-to-Chinese translations and corresponding questions, and the results showed that the proposed approach was effective in generating relevant and informative questions.

In [26] conducted an empirical study to evaluate the effectiveness of interactive machine translation with automatic question generation. The study utilized a prototype system that integrated automatic question generation with a machine translation system, and evaluated the system on a dataset consisting of English-to-Chinese translations and corresponding questions. The results showed that the interactive machine translation system with automatic question generation was effective in improving translation quality and user satisfaction.

In [27] proposed a knowledge graph-based approach for cross-lingual question answering in machine translation. The proposed approach utilized a multilingual knowledge graph and a graph-based neural network for question answering, and was evaluated on a dataset consisting of questions and answers in English, Chinese, and French. The results showed that the proposed approach was effective in answering questions across different languages.

In [28] proposed an interactive machine translation system with automatic question generation and ranking, which aimed to improve the efficiency and accuracy of machine translation. The proposed system utilized a neural machine translation model, a question generation model, and a question ranking model, and was evaluated on a dataset consisting of English-to-Chinese translations and corresponding questions. The results showed that the proposed system was effective in generating relevant and informative questions, and in improving the overall translation quality.

Several techniques are implemented with the feature extraction-based opinion mining consideration of different methods and techniques to perform text classification. It is not effective for sentimental analysis with likes and dislikes for analysis to achieve characteristics those are subjective

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and linguistic to evaluate the association between words and sentiments related to opinion.

III. Research Methodology

To evaluate the opinion of Q & A is evaluated based on the Conditional Random Field integrated with the bi-gram classifier model. The constructed model performs the discriminative analysis with the time-domain Machine Learning model. The proposed CRFDA model determines the detection event for the test and the tagging through TempEval-2. The proposed CRFDA model focused on estimation of words with the opinion of Q & A. The features used in the Q&A statement are initially classified using a machine learning model within the proposed CRFDA model. Using WordNet and custom-built rules, the sematic role labeller is used to enhance the CRFDA model's performance in terms of data extraction. The proposed CRFDA model estimates the conditional probability value for the designated output values for the designated input values. The state sequence $S = < S1, S2, \ldots..ST >$ based on the observation sequence $O = < O1, O2, \ldots.., OT >$ calculated using the equation (1)

$$P^{(S|O)} = \frac{1}{z_0} exp(\sum_{t=1}^{T} \sum_{k=1}^{K} \lambda_k f_k(st-1, st, O, t)) \quad (1)$$

In the above equation (1), the feature function is stated as $f_k(st-1, st, O, t)$ with the weights λ_k utilized for the data training. The feature function values are in the range between $- \propto + \propto$ ..... , but in the binary form. To derive the conditional probabilities the sum up values are represented as 1 with the normalization factor value defined in equation (2)

$$z_0 = \sum_s exp\,(\sum_{t=1}^{T} \sum_{k=1}^{K} \lambda_k f_k(st-1, st, O, t)) \quad (2)$$

Through the dynamic process CRFDA model compute the dynamic programming process in the Hidden Markov Model process.

3.1 Event Extraction Rules

The opinion of the Q & A is collected in the form of text and audio file to evaluate the expressions. The proposed CRFDA model concentrated on the extraction of opinion of Q & A with identification of lexical classes such as ‘agree’ and ‘disagree’. The prefix morphological deverbal derivations are mentioned as ‘ag-‘and ‘dis-‘. At first, the Stanford Named Entity tagger and the TempEval-2 benchmark dataset form the basis of the proposed CRFDA model. The Person, Location, Organization, and Other Classes are used to assess the effectiveness of the system's output tagger. The capital letter of the words is started with the capital letter name entity (Nes). Through the consideration of following rules, the events are extracted:

Case 1: The morphological derived nouns are derived from the verb those are distinguished based on nominalizations. The deverbal nouns are identified based on consideration of suffixes such as “-tion”, “-ion”, “-ing” and “ed” and so on. Non-Nes nouns with suffixes are categorized as "word events" in this context.

Case 2: Within the test set the verb-noun combination are searched for the NE word token event count.

Case 3: Through consideration of aspectual prepositions with consideration of nominals and non-deverbal event nouns. The prepositions are evaluated based on during, after, before and complex prepositions those are beginning to end. The next word located to the word or phrase are considered as the events.

Case 4: The occurring of non-NE are evaluated based` on the frequency expressions based on occurrence and period probably with the event nouns.

Case 5: The event nouns are appeared as the aspectual objects related to time in terms of verb those begun campaign or carried out campaign so on. The non-NEs those appear with expression are presented as “have begun a”, “have carried out a” and so on is considered as the events.

Table 1: Training Data for the Events

Relation	**Overlap**	**Overlap**	**overlap**	**Before**
Part of speech	Verb	Verb	adjective	Verb
Class	Reporting	I_action	reporting	Reporting
Aspect	None	Perfective	none	None
Tense	Present	Past	past	Past
<mainevent,subevent, mainevent,subevent>	<e26,e28>	<e6,e15>	<e19,e28>	<e30,e35>
Part of Speech	Noun	Verb	verb	Verb
Class	I_action	Occurrence	reporting	Occurrence
Aspect	None	Perfective	none	None
Tense	None	Past	past	Past
E_id	e28	e15	e28	e35
Part of Speech	Verb	Noun	verb	Adjective
Class	occurrence	State	occurrence	I_action

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Aspect	perfective	None	none	None
Tense	present	None	none	None
E_id	e27	e7	e23	e33
Part of speech	Verb	Verb	verb	Verb
Class	Occurrence	I_action	occurrence	Occurrence
Aspect	perfective	None	perfective	Perfective
Tense	present	Prespart	past	Past
E_eid	e30	e16	e29	e38

Table 2: Sample of the Training Data for the Event

Relation	**Overlap**	**Overlap**	**Overlap**	**before**
Part of Speech	Verb	Verb	Adjective	verb
Class	Reporting	I_action	Reporting	reporting
Aspect	None	Perfective	None	none
Tense	Present	Past	Past	past
<mainevent, mainevent>	<e26,e28>	<e6,e15>	<e19,e28>	<e30,e35>
Part of Speech	Verb	Verb	Verb	verb
Class	occurrence	I_action	Occurrence	occurrence
Aspect	Perfective	None	Perfective	perfective
Tense	Present	Prespart	Past	past

The table 1 and 2 provides the event data for the sample training consideration of subordinate event related to main event. The TempEval – 1 is estimation of the event relation through consecutive sentences. The example of the event sentence is considered as the main event based on the syntactic based criteria for the sentence. It can be syntactical subordinate event based main-event dominated coordination relation for the sentences. The CRFDA model perform the temporal tagging based on the supervised based statistical learning algorithm based on the Conditional Random Field (CRF). The temporal relation identification is performed based on the pair-wise classification with target pair EVENT and EVENT tag modelled with CRF. The proposed CRFDA examine the relationship between adjacent verb based sentences related to events. The temporal Expression (TEs) based events are annotated based on the standard machine Learning (ML). The temporal relationship between variables are predicted based on the consideration of features such as OVERLAP, BEFORE, AFTER, BEFORE-OR- OVERLAP, OVERLAP-OR-AFTER and VAGUE. Furthermore, event expression are evaluated with the occurred process for the annotation training and testing of the temporal relations.

Features and Description

The proposed CRFDA model uses the gold-standard based TimeBank feature estimation model the event training with the CRF model. The present model focused on combination of different features those are presented as follows:

1. **Event Class:** The “EVENT” tag feature is annotated by the text element with the semantic events.
2. **Event stem**: It represents the head event stem
3. **Event and strings:** The actual event string and information about time are computed.
4. **Event terms Part of Speech (PoS):** It represent the information of event based on consideration of feature PoS values in terms of NOUN, ADJECTIVE and PREP, VERB.
5. **Event tense**: Through the standard distinction capture the grammatical verbal phrases are categorized based on the consideration of attributes presented as PRESPART, INFINITIVE, PRESENT, PAST, FUTURE, PASTPART, or NONE.
6. **Event aspect**: It represents the events based on consideration of attributes represented for the events. The attributes aspects comprises of the different values such as PERFECTIVE, PROGRESSIVE, and PERFECTIVE PROGRESSIVE or NONE.
7. **Event polarity**: The event instance polarity is computed with the Boolean values either as POSITIVE or NEGATIVE.
8. **Event modality**: The attribute modality is in the modal word for the modified instances.
9. **Type of temporal expression**: The expression of temporal feature evaluate the relations, holding events, between expressions or between event and event time.
10. **Temporal signal**: It denotes the temporal prepositions.
11. **Temporal relation between creation time and target sentence**: The feature value are denoted as “*greater than*”, “*less than*”, “*equal*”, or “*none*”.

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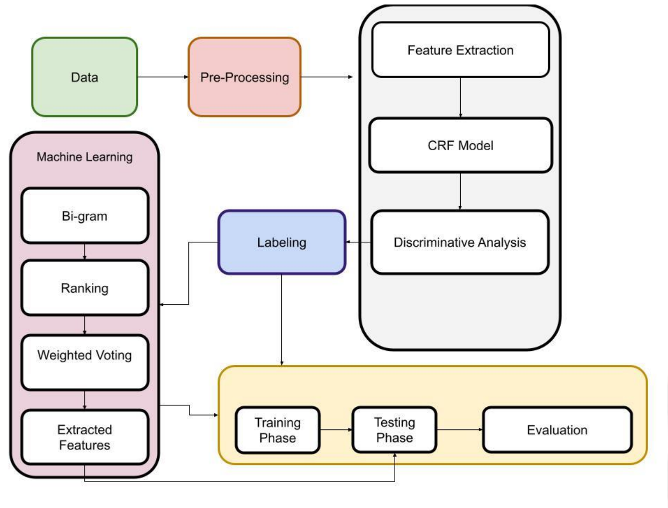

Figure 1: Process in CRFDA

3.2 Evaluation Scheme

The performance of the proposed CRFDA model evaluate the temporal relations for the three disjunctions for the different set represented as BEFORE, OVERLAP, and AFTER and EFORE-OR-OVERLAP, OVERLAP-OR-AFTER and VAGUE. The disjunction increases in the addition question are related to the score value based on the BEFORE with the key value of BEFORE-OR-OVERLAP. The proposed CRFDA model uses the voting scheme with two schemes such as strict and relaxed. In the process of the strict scoring the exact matches with the success are considered. In this case, if key is considered as the OVERLAP and the response of BEFORE-OR-OVERLAP is considered as 'failure'. With the scoring scheme of relaxed value the occurrence key is evaluated with 'OVERLAP' response 'BEFORE-OR-OVERLAP' considered as the 'success'. The strict scoring procedure utilized for the precision and recall are presented in equation (3) and equation (4)

$$Precision = \frac{RC}{R} \quad (3)$$

$$Recall = \frac{RC}{K} \quad (4)$$

In the above equation (3) and (4) the response correct answer is denoted as RC, the total answer response is defined as R and the total number of answer key is defined as K. The relaxed score computed for the precision and recall is defined as in equation (5) and (6)

$$Precision = \frac{RCw}{R} \quad (5)$$

$$Recall = \frac{RCw}{K} \quad (6)$$

Where, the correct answer weights are represented as RCw. The relaxed scoring with the partial matches are measured based on the consideration of F-measure value presented as in equation (7) and (8)

$$Pr = Precision\ and\ Re = Recall \quad (7)$$

$$F - measure = 2Pr * Re/(Pr + Re) \quad (8)$$

IV. Experimental Result and Discussions

The proposed CRFDA comprises of the feature to estimate the features based on the consideration of available extracted feature vector in every pair of TimeBank Corpus. The analysis is based on the consideration of the training data as the (W_i, T_i), where, $W_i$is the i^{th}pair feature vector and TempEval relation class is denoted as the T_i. The feature templates are built on the basis of the training data. The training procedure implemented for the proposed CRFDA model is presented as follows

1. Set the corpus training, C.
2. Extract corpus training based on estimation of relations
3. Create a file features, comprises of the lexical features for the corpus training
4. Define a template features.
5. Estimate the weights λk in CRF for the every fK based on training file and template feature as input.
6. Use performance estimation to derive the efficient feature template.
7. Pick the most useful part of the provided templates.
8. Reformat the CRF model

Table 3: Evaluation for event-time identifier

Technique	Evaluation scheme	Precision	Recall	F-measure
Baseline	Strict	0.568	0.568	0.568
	Relaxed	0.589	0.589	0.589
CRF	Strict	0.598	0.598	0.598
	Relaxed	0.611	0.611	0.611
CRFDA	Strict	0.61	0.61	0.61
	Relaxed	0.63	0.63	0.63

The table 3 provides the event-time identifier model based on the consideration of different data evaluated with the **TimeBank** datasets. The event-time relation comprises of the test data with 169 event link such as OVERLAP-99, AFTER-30, BEFORE-21, NON-RELATED-13, OVERLAP-OR-AFTER-4 and BEFORE-OR-OVERLAP-2. Precision, recall, and F-measure are taken into account to assess the efficacy of the proposed CRFDA. The scoring for the variables is conducted based on the consideration of two scoring scheme such as strict and relaxed. The exact matches are estimated with the strict scoring and relaxed scoring provides the credit based on the partial semantic matches. The developed CRFDA model comprises of the

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variable available features in the model as presented in table 4. The simulation results illustrated that CRF based event-time identification of relations. The features are computed based on the temporal words for the time strings with the temporal signal, expression and sentence. There is a tight scheme of 59.8%, 59.8%, and 59.8% for the precision, recall, and F-measure value in the proposed CRFDA model. Precision, recall, and F-measure are all provided at 61.1% in the lenient grading method. It is presented that Precision, Recall and F-measure significant performance based on classification accuracy.

Table 4: CRFDA Analysis

	Evaluation result of SVM using feature combination on Tempeval-2	Evaluation result of CRF using different feature combination on Tempeval-2
Feature Combination	Results	Results
Context, Tense, Aspect	0.619	0.63
Context, Aspect, POS	0.573	0.591
Context, Tense, Aspect, combination of derived feature	0.638	0.649
Context, Tense, POS	0.601	0.619

The results of the study showed that the proposed CRFDA model achieved a classification accuracy of 64.9%. Accurate feature vectors include the present token and PoS, as well as combinations of PoS and current token tenses, PoS and current token polarity, PoS and current word integration, PoS integration with current token tense value, temporal expression, signal, and target sentences, and PoS integration with current word integration. In table 5 combination of feature based on strict and relaxed state are presented.

Table 5: Comparison of Features

Feature Combination	**Strict**			**Relaxed**		
	Pr	Re	F-measure	Pr	Re	F-measure
Context, Tense, Aspect, dynamic information	0.438	0.438	0.438	0.469	0.469	0.469
Context, Tense, POS	0.40	0.40	0.40	0.41	0.41	0.41
Context, Tense, Aspect	0.41	0.41	0.41	0.42	0.42	0.42
Context, Aspect, POS	0.30	0.30	0.30	0.32	0.32	0.32

Table 6: Evaluation with various feature combinations (main event)

Feature Combination	**Strict**			**Relaxed**		
	Pr	Re	F-measure	Pr	Re	F-measure
Context, Tense, Class and dynamic information	0.551	0.551	0.551	0.569	0.569	0.569
Context, Tense, Aspect	0.48	0.48	0.48	0.51	0.51	0.51
Context, Tense, Class	0.51	0.51	0.51	0.53	0.53	0.53
Context, Aspect, Class	0.39	0.39	0.39	0.41	0.41	0.41

Table 7: Evaluation with various feature combinations (subordinate event)

Technique	**Strict**			**Relaxed**		
	Pr	Re	F-measure	Pr	Re	F-measure
CRF (main-event)	0.438	0.438	0.438	0.469	0.469	0.469
CRF(subordinate-event)	0.551	0.551	0.551	0.569	0.569	0.569
Baseline	0.42	0.42	0.42	0.46	0.46	0.46
LCC-TE(Best System)	0.55	0.55	0.55	0.58	0.58	0.58

The temporal relation in the system feature extraction are represented in the features are presented in table 6 and table 7 based on consideration of main-event and sub-ordinate event techniques. The table 6 provides the main-event performance technique related to the size such as previous state, present state and next two state such as main event pairs, tense and features. The values of the severe evaluation's prevision, recall, and F-measure are reported as 43.8%, 43.8%, and 43.8%, while the values of the relaxed evaluation are 46.9%, 46.9%, and 46.9%.

Tables 8 and 9 show the overall evaluation metrics for the CRFDA model's primary event using temporal identification. The table 10 provides the CRF-based evaluation results compared with the SVM system for the subordinate event estimation to examine the temporal relation for the identification of tasks.

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Table 8: Overall evaluation results

Model Features	**TempEval-1 Dataset**						**TempEval-2 Dataset**
Feature List is run on CRF based classifier.	Precision Strict	Precision Relaxed	Recall Strict	Recall Relaxed	F-measure Strict	F-measure Relaxed	Accuracy
TimeML gold standard features: word, pos, class, tense, polarity, aspect and modality	55.1	56.9	55.1	56.9	55.1	56.9	0.56
TimeML gold standard features + relational context	55.5	57.3	55.5	57.3	55.5	57.3	0.57
TimeML gold standard features + relational context + modal context	56.4	58.2	56.4	58.2	56.4	58.2	0.59
TimeML gold standard features + relational context +modal context+ Ordered based context	56.8	58.6	56.8	58.6	56.8	58.6	0.60
TimeML gold standard features + relational context + modal context+ Ordered based context+ Co-referencebased feature	59.2	61.1	59.2	61.1	59.2	61.1	0.63
TimeML gold standard features + relational context +modal context+ Ordered based context+ Co-reference based feature+ Event-DCT relation based feature	60.1	61.9	60.1	61.9	60.1	61.9	0.64
TimeML gold standard features + relational context +modal context+ Ordered based context+ Co-reference based feature+ Event-DCT relation based feature+Preposition Context	61.2	63.1	61.2	63.1	61.2	63.1	0.65

Table 9: Estimation of Features

Model Features	**TempEval-2Dataset**	
Feature List is run on CRF and SVM based classifier.	Accuracy for CRFDA	Accuracy for SVM
TimeML gold standard features: word, pos, class, tense, polarity, aspect and modality	0.88	0.58
TimeML gold standard features + relational context	0.89	0.59
TimeML gold standard features + relational context + modal Context	0.90	0.60
TimeML gold standard features + relational context + modal context+ Ordered based context	0.93	0.63
TimeML gold standard features + relational context + modal context+ Ordered based context+ Co-reference based feature	0.95	0.64
TimeML gold standard features + relational context + modal context+ Ordered based context+ Co-reference basedfeature+ Event-DCT relation based feature	0.96	0.65
TimeML gold standard features + relational context + modalcontext+ Ordered based context+ Co-reference based feature+ Event-DCT relation based feature+ Preposition Context	0.98	0.66
TimeML gold standard features + relational context + modalcontext+ Ordered based context+ Co-reference based feature+ Event-DCT relation based feature+ Preposition Context+ Context word before or after temporal expression	0.99	0.67
TimeML gold standard features + relational context + modalcontext+ Ordered based context+ Co-reference based feature+ Event-DCT relation based feature+ Preposition Context+ Context word before or after temporal expression + Stanford parser based clause boundaries features	0.91	0.69

The weights are computed based on the voting value with consideration of different classification model. The model comprises of the main event and sub-event for the evaluation with the benchmark dataset TempEval-1 and TempEval-2 as presented in table 10 and table 11 respectively.

Table 10: Estimation of Precision and Recall

Dataset	TempEval-1			TempEval-2
Model	**Precision**	**Recall**	**F-measure**	**Accuracy**
CRF [Best]	64.5 66.4	64.5 66.4	64.5 66.4	0.68
SVM[Best]	63.3 65.1	63.3 65.1	63.3 65.1	0.67
Majority voted	64.5 66.2	64.5 66.2	64.5 66.2	0.69
CRFDA	84.9 86.9	84.9 86.9	84.9 86.9	0.90

The table 11 provides the comparative examination of classification accuracy for the estimation of main-event.

Table 11: Comparison of Accuracy

Model	Accuracy
CRF [Best]	0.71
SVM[Best]	0.69
Majority voted	0.73
CRFDA	0.91

The comparative analysis expressed that the proposed CRFDA model achieves the accuracy value of 0.94, which is significantly higher than the conventional CRF, SVM and majority voting model.

V. Conclusion

This paper presented the machine learning-based method for the estimation of event identification task relationship estimation based on the consideration of TempEval (1,2) framework with translation robots to perform Q&A interaction. The one task is identified based on consideration of six different relations based on consideration of two main consecutive events sentences and other six different relations are identified with the two sub events with the syntactical event. The CRFDA model uses the available features based on the TimeBank based corpus for the feature derivative text. The discriminative analysis model is utilized based on the combination of event relation based feature for the task identification. Simulation analysis expressed that competitive analysis of the system is evaluated with the TempEval (1.2). The event temporal relation is evaluated for the identification of task with supervised machine learning model with the CRF system for the identification of feature for the dataset training. Finally, with the integration of classifier weighted voting based technique is utilized for the task identification. The voting model comprises of the contextual information for the feature TimeBank for the derived contextual information features. The main event identification demonstrated that proposed CRFDA model achieves the classification accuracy of 66.9% and 70% and the weighetd voted model CRF achieves 66.4% and 68%, SVM with 65.1% and 67% on TempEval-1 and TempEval-2 datasets, respectively. The sub event relation demonstrated tha accuracy is achieved as the 94% with the weighted voting model CRF as 91%, SVM value of 69% for the data.

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