Neuro-Fuzzy Based Model for Phrase Level Emotion Understanding

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***Abstract*—**The present approach deals with the identification of Emotions and classification of Emotional patterns at Phrase-level with respect to Positive and Negative Orientation. The proposed approach considers emotion triggered terms, its co-occurrence terms and also associated sentences for recognizing emotions. The proposed approach uses Part of Speech Tagging and Emotion Actifiers for classification. Here sentence patterns are broken into phrases and Neuro-Fuzzy model is used to classify which results in 16 patterns of emotional phrases. Suitable intensities are assigned for capturing the degree of emotion contents that exist in semantics of patterns. These emotional phrases are assigned weights which supports in deciding the Positive and Negative Orientation of emotions. The approach uses web documents for experimental purpose and the proposed classification approach performs well and achieves good F-Scores.

***Keywords*—**Emotions, sentences, phrases, classification, patterns, fuzzy, positive orientation, negative orientation.

I. Introduction

EMOTIONS have been widely studied in psychology and behavioral sciences, as they are considered as an important element of human nature. It represents the psychological state of a person which is normally based on internal factors such as mental and physical status of a person and external factors say, social sensory feeling [15]. Identifying emotions from natural language texts has drawn the attention of several information processing communities since, it plays a vital role in human intelligence, decision making, social interaction, awareness, learning, creativity, etc. Analysis of the emotional content in text, determines opinions, attitudes, evaluations and inclinations. Also, researchers have focused in the field of human computer interaction namely facial expressions studies, recognition of emotions using sensors, opinion mining and market analysis, etc. In future, human-computer interaction is expected to emphasize the naturalness and effectiveness by integrating the models of human cognitive capabilities that includes emotional analysis and generation. Several efforts have been made by the natural language processing researchers to identify emotion at different level of granularities say word, sentence or document using reviews, news, question answering, information retrieval, etc. Nowadays, news websites and news channels have provided a new service that allows users to express their emotions after browsing news articles. This has focused on recognizing positive and negative orientations of a person with respect to interested articles. For each article, the readers express their emotions through voting for a set of predefined emotion labels/tags.

In general, six emotions such as *anger, fear, sad, disgust, happy, surprise* [5] can be expressed in human beings and certain eventual situations can be expressed in certain possible manners. In many events, such expressions contain very little or sometimes no affect-related words and simply they describe the experiences which can be deciphered by the audience [6]. Existing models of emotion detection are able to find affect related direct expressions. The use of knowledge-rich dictionaries supports in classification. For instance, *I am very happy*, *I am bit angry*, etc., contain words like *happy, angry* with corresponding affective meaning in dictionaries. Instances containing negations, such as *I am not happy* conveys the definition of inverse emotions and corresponding rules to pass from one emotion to the other. Certain instances are more difficult to classify by dictionary-based models such as *I am celebrating my 25th marriage anniversary*, which can be labeled with *joy.* Such instances would perhaps be classifiable through a supervised system, which would know that the bigram *marriage anniversary* is associated for the sentences related to *joy*. A method is proposed by [3] in which the main idea is to obtain the knowledge of emotions that are related to different eventual concepts. In this process, the system learns that this specific bigram *marriage anniversary* relates to the *joy* emotion, and also it learns that the eventual concepts related to *anniversary/parties/birthdays/marriages* are related to emotion *joy* in general. These approaches solve the problem of indirectly mentioning an emotion by using the eventual concepts that are related to it instead. However, some instances would also fail to classify clearly the emotion expressed in more complex settings, such as *If my husband hadn't expired, today we would be celebrating our 25th marriage anniversary*, where the inverse emotion works and express the feel of *sad.* Thus, as it is observed that the presence of concepts in the text cannot be considered as a mark that the respective sentence directly contains that emotion. Thus, the events also play equally important role in emotion classification.

The rest of the paper is organized as follows. The related work is presented in the next section and proposed work is presented in Section III. Experimental results are presented in Section IV. The paper is concluded in the last section.

II. Background

Nowadays, research works focus on analyzing online users' sentiment responses while they are exposed to news articles which are called as social emotions [1]. The first line of

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research related to this direction is from the task of ''Affective Text'' in SemEval-2007 [13], where a corpus of news headlines extracted from Google news and CNN was provided. The task aimed at exploring the connection between news headlines and the evoked emotions of readers, in which three systems were introduced: SWAT, UA and UPAR7. The system SWAT [8] proposed a supervised approach by developing a word-emotion mapping dictionary which is used to score each word of a headline to have an average score for the headline and to decide its emotion. In the system UA [13], the approach gathered statistics from three search engines and computed the Pointwise Mutual Information (PMI) scores, to determine the emotion labels of headlines. The system UPAR7 [2] was a rule-based system which mainly relies on syntactic parser and lexicons. It uses linguistic and rule based approach to tag news headlines for Ekmans predefined emotions and for polarity such as Positive or Negative. The algorithm used existing emotion lexicons such as WordNet-Affect and SentiWordNet. A similar module of research work was also conducted based on emotion lexicons such as Subjectivity Wordlist, WordNet-Affect and SentiWordNet, so as to identify event and sentiment expressions at word level from the sentences of TempEval-2010 corpus [9]. However, due to the limited words in the news headlines or sentences, these approaches faced the problem in emotion analysis and detection. A model is proposed in Neviarouskaya et al. [11] to estimate the emotions in text by considering the relations among words in a sentence and uses symbolic clues as well as natural language processing techniques for word/phrase/sentence level analysis. Identifying emotion understanding the importance of Verbs and Adjectives has been proposed by Vincent, et al. [14], which is topic and genre independent. Here, each post from a blog has been classified as objective, subjective-Positive and subjective-Negative. Yahoo! Kimo Blog has been used as corpora in the method proposed by Ekbal and Bandyopadhyay [7] to build emotion lexicons. Emoticons were used to identify emotions associated with textual keywords. A system has been proposed for classifying news articles according to the reader's emotions [10]. Emotion classification task on web blog corpora using SVM and CRF machine learning techniques is carried out. It has been observed that the CRF classifiers outperform SVM classifiers in case of document level emotion detection. In [12], characterization of words and phrases according to their emotive tone has been described. The system classifies the reviews into two types, namely recommended and not recommended using the semantic Orientation of the phrases in the review. However, in many domains of text, the values of the individual phrases may bear little relation to the overall sentiment expressed by the text. In [4], emotions are extracted based on WordNet Affect list and dependency relations using intensities. The SVM based supervised framework is employed by incorporating different word and context level features. In [5], emotion analysis on blog texts has been carried out on the English SemEval 2007 affect sensing corpus containing only news headlines. Conditional Random Field (CRF) based classifier has been applied for recognizing six basic emotion tags for different words of a sentence. A score based technique has been adopted to calculate and assign tag weights to each of the six emotion tags. Since, emotion is subjective entity and a sentence may have multiple emotions, classifying the sentence based on the mood is a hard task and above mentioned approaches in sentence classification achieve only modest performance in this domain.

It is observed that the most of the above discussed machine learning based models have considered sentence as their basic key constituent and the phrases are given less weightage in the sentences. In our approach, like words, phrases are considered as the semantic units for emotional expressions and are used in identifying emotional patterns. We mainly focus on the characteristics of emotional triggered (*ET)* terms and the role of co-occurrences of *ET* term in the phrase. We consider phrasal patterns that effectively contributes for Positive and Negative Orientation of emotions in a sentence. Here, the proposed approach considers the POS features of *ET* terms and its co-occurrence terms. A supervised framework is employed for classifying the emotional phrases. The presented approach performs well and achieves encouraging results in classification.

III. Proposed Approach

Analysis of human emotions in text is considered as a pattern identification and classification problem. The main objective of the proposed approach is to identify the patterns of human emotions with respect to Positive and Negative Orientation.

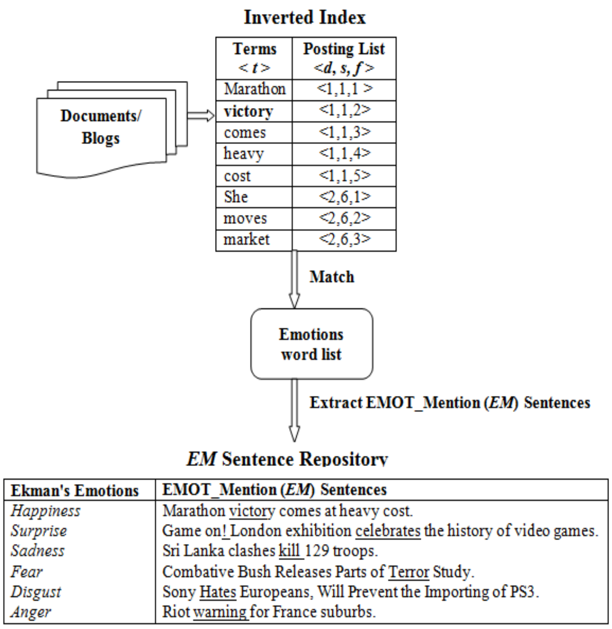

Fig. 1 EMOT-Mentions Repository from Inverted Index

The documents related to various emotions are considered and analyzed. It is known that the sentences in the documents are constructed using terms/tokens. These sentences are tokenized and inverted index is constructed. As the sentences in the documents are built up with large number of terms, only certain terms represent the emotions and referred as EMOT-Triggers (*ET*). These terms exhibit the degree of emotional constituents along with other surrounding related hints. We use synonyms, hyponyms, hypernyms to extract seed EMOT-Triggers from the inverted index. Later, extracted seed EMOT-Triggers along with their associated sentences (*s*) are extracted which are referred to as EMOT-Mentions (*EM*) and maintained in the repository. This is represented in Fig. 1. Rest of the sentences are considered as Neutral sentences and neglected. Further, the EMOT-Mentions are processed for Part of Speech (POS) Tagging for analyzing the patterns related to various emotions. This is represented in Table I.

TABLE I
POS TAGGED EMOT-MENTIONS

EMOT-Triggers	POS Tagged EMOT-Mentions
Victory	Marathon/NN victory/NN comes/VBZ at/IN heavy/JJ cost/NN ./.
Clashes	Sri/NNP Lanka/NNP clashes/NNS kill/VBP 129/CD troops/NNS./.
Hates	Sony/NNP hates/VBZ europeans/NNS ,/, will/MD prevent/VB the/DT importing/NN of/IN PS3/NNP ./.

In our approach, we have considered four significant POS Tags such as Adverbs, Adjectives, Verbs, Nouns for describing EMOT-Triggers in the sentences. In addition, we consider EMOT-Actifier Tags such as Intensifiers, Negations, Interjections, Conjunctions for identifying the degree of emotions. Using both of these Tags, the EMOT-Mentions classification is done using decision tree.

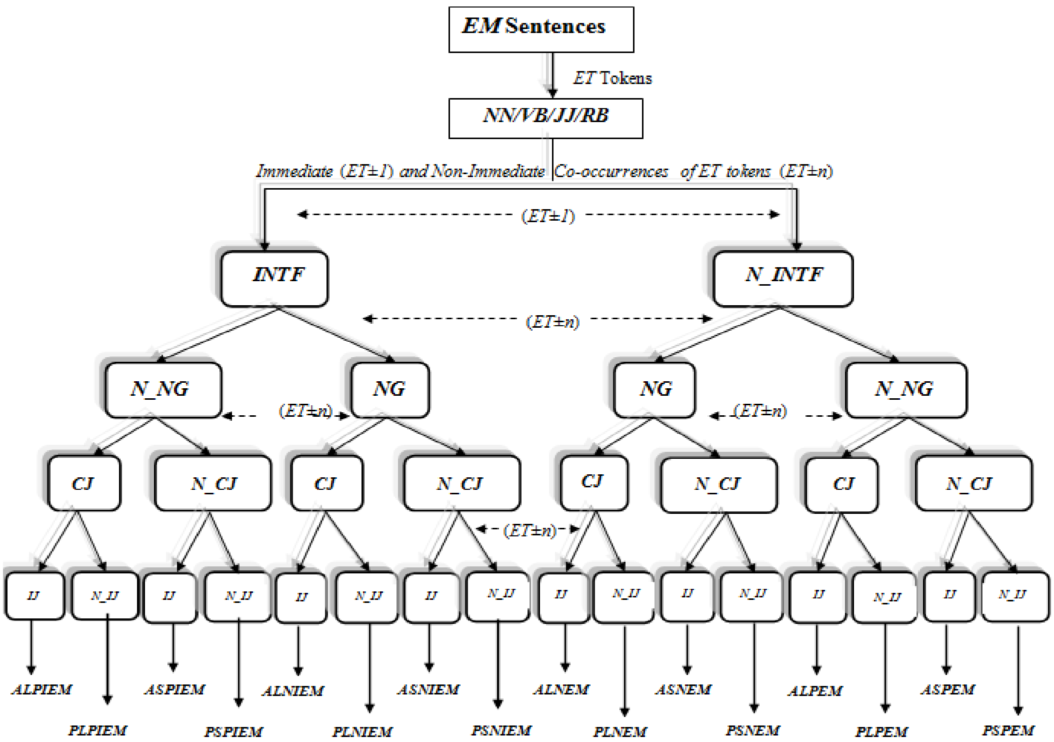

Fig. 2 Hierarchical EMOT-Mention Classification using Decision Tree

In the first level of classification, the POS feature of EMOT-Triggers are considered, which can be appeared as one among the POS Tags (Noun/Verb/Adjective/Adverb) in the sentences. In the second level, immediate co-occurrence terms of the EMOT-Triggers (*ET±1*) are considered and verified for the presence of Intensifiers. In the third level, co-occurrence terms of the EMOT-Triggers (*ET±n*) are considered and verified for the presence of Negations. In the fourth level, co-occurrence terms of the EMOT-Triggers (*ET±n*) are considered and verified for the presence of Conjunctions in the sentence. In the last level, Interjections are considered for the classification. These words can be placed before or after a sentence (*ET±n*) followed by exclamation mark or punctuation mark. Thus, the Tag based hierarchical approach classifies the EMOT-Mentions into 16 patterns at sentence level. The EMOT-Mentions contain sentences with mixed emotions well as sentences having single emotion. The classification rules are validated using CART tool. This is represented in Fig. 2. The tool easily classifies Positive and Negative Orientation for the EMOT-Mentions having single emotions.

It is observed that the rules are failed to clearly define Positive and Negative Orientation for the EMOT-Mentions having mixed emotions. As a result, ambiguity and impreciseness between the patterns exist and affects the classification accuracy by increasing misclassification rate. In general, mixed emotions occur in lengthy sentences having many phrases. Hence the EMOT-Mentions sentences are broken at phrase level and referred as EMOT_phrasals.

Further, the rules are refined at phrase level using fuzzy approach. The fuzzy rules are applied to classify the patterns at EMOT_Phrasal level.

A. Fuzzy Rule at Phrase-Level Classification

EMOT-Mentions having single phrases are referred as Simple Phrased EMOT-Mentions (***S^P^EM***) and EMOT-Mentions having multiple phrases are referred as Complex Phrased EMOT-Mentions (***C^P^EM***). We constructed the fuzzy rules for both ***S^P^EM*** and ***C^P^EM*** EMOT-Mentions. The EMOT-Mentions are primarily verified for the class they belong i.e. ***S^P^EM*** and ***C^P^EM*** class then later EMOT-Phrases are verified using FOR loop for various patterns.

Rule: If (*EM=CJ*) && (*EM= ET*) && (*ET=NN/VB/JJ/RB*) then ***S=C^P^EM***
{
For ($p_1, p_2, \ldots, p_m$)
{
Rule 1: If (*ET±1=INTF*) && (*ET±n=N_NG*) && (*ET±n=IJ*) then ***C=ALPIEp***
Rule 2: If (*ET±1=INTF*) && (*ET±n=N_NG*) && (*ET±n=N_IJ*) then ***C=PLPIE_P***
……………………………….
}

The fuzzy rules for ***S^P^EM*** and ***C^P^EM*** classes are represented in Tables II (A) and (B). ANFIS model is used as tool to validate the rules. Based on the features of EMOT_Phrasals and their structure in the sentence and also using the knowledge of previous hierarchical classification, intensity grades are estimated for the EMOT_Phrasals patterns. These intensity grades classify the patterns of EMOT_Phrasals into Positive and Negative Orientation. Both ***S^P^EM*** and ***C^P^EM*** classes play individual role in representing these emotional orientations.

TABLE II (A)
FUZZY RULES FOR ***S^P^EM*** PHRASAL PATTERNS

Rule A: If (*EM=N_CJ*) && (*EM= ET*) && (*ET=NN/VB/JJ/RB*) then ***EM=S^P^EM***
{
For ($p_1, p_2, \ldots, p_m$)
{

S^P^EM **Patterns**	**Fuzzy rules**	**Linguistic Grades**
ASPIE_P	(*ET±1=INTF*) && (*ET±n=N_NG*) && (*ET±n=IJ*)	*Positive Emotions Low (P_EL)*
PSPIE_P	(*ET±1=INTF*) && (*ET±n=N_NG*) && *ET±n=N_IJ*)	*Positive Emotions Very Low (P_EVL)*
ASNIE_P	(*ET±1=INTF*) && (*ET±n=NG*) && (*ET±n=IJ*)	*Negative Emotions Low (N_EL)*
PSNIE_P	(*ET±1=INTF*) && (*ET±n=NG*) && (*ET±n=N_IJ*)	*Negative Emotions Very Low (N_EVL)*
ASPE_P	(*ET±1=N_INTF*) && (*ET±n=N_NG*) && (*ET±n=IJ*)	*Positive Emotions Poor (P_EP)*
PSPE_P	(*ET±1=N_INTF*) && (*ET±n=N_NG*) && (*ET±n=N_IJ*)	*Positive Emotions Very Poor (P_EVP)*
ASNE_P	(*ET±1=N_INTF*) && (*ET±n=NG*) && (*ET±n=IJ*)	*Negative Emotions Poor (N_EP)*
PSNE_P	(*ET±1=N_INTF*) && (*ET±n=NG*) && (*ET±n=N_IJ*)	*Negative Emotions Very Poor (N_EVP)*

TABLE II (B)
FUZZY RULES FOR ***C^P^EM*** PHRASAL PATTERNS

Rule B: if (*S=CJ*) && (*S= ET*) && (*ET=NN/VB/JJ/RB*) *then* ***S=C^P^EM***
{
For ($p_1, p_2, \ldots, p_m$)
{

C^P^EM **Patterns**	**Fuzzy rules**	**Linguistic Grades**
ALPIE_P	(*ET±1=INTF*) && (*ET±n=N_NG*) && (*ET±n=IJ*)	*Positive Emotions Very High (P_EVH)*
PLPIE_P	(*ET±1=INTF*) && (*ET±n=N_NG*) && (*ET±n=N_IJ*)	*Positive Emotions High (P_EH)*
ALNIE_P	(*ET±1=INTF*) && (*ET±n=NG*) && (*ET±n=IJ*)	*Negative Emotions Very High (N_EVH)*
PLNIE_P	(*ET±1=INTF*) && (*ET±n=NG*) && (*ET±n=N_IJ*)	*Negative Emotions High (N _EH)*
ALPE_P	(*ET±1=N_INTF*) && (*ET±n=N_NG*) && (*ET±n=IJ*)	*Positive Emotions Medium (P_EM)*
PLPE_P	(*ET±1=N_INTF*) && (*ET±n=N_NG*) && (*ET±n=N_IJ*)	*Positive Emotions Lower Medium (P_ELM)*
ALNE_P	(*ET±1=N_INTF*) && (*ET±n=NG*) && (*ET±n=IJ*)	*Negative Emotions Medium (N_EM)*
PLNE_P	(*ET±1=N_INTF*) && (*ET±n=NG*) && (*ET±n=N_IJ*)	*Positive Emotions Lower Medium (N_ELM)*

***ALPIE_P*:** Active Long Positive Intensified EMOT_Phrase, ***PLPIE_P*:** Passive Long Positive Intensified EMOT_Phrase, ***ALNIE_P*:** Active Long Negative Intensified EMOT_Phrase, ***PLNIE_P*:** Passive Long Negative Intensified EMOT_Phrase, ***ALPE_P*:** Active Long Positive EMOT_Phrase, ***PLPE_P*:** Passive Long Positive EMOT_Phrase, ***ALNE_P*:** Active Long Negative EMOT_Phrase, ***PLNE_P*:** Passive Long Negative EMOT_Phrase, ***ASPIE_P*:** Active Short Positive Intensified EMOT_Phrase, ***PSPIE_P*:** Passive Short Positive Intensified EMOT_Phrase, ***ASNIE_P*:** Active Short Negative Intensified EMOT_Phrase, ***PSNIE_P*:** Passive Short Negative Intensified EMOT_Phrase, ***ASPE_P*:** Active Short Positive EMOT_Phrase, ***PSPE_P*:** Passive Short Positive EMOT_Phrase, ***ASNE_P*:** Active Short Negative EMOT_Phrase, ***PSNE_P*:** Passive Short Negative EMOT_Phrase.

IV. EXPERIMENTAL RESULTS

For evaluating the proposed approach, the web Corpus is constructed which has collection of articles and used as a database. These articles have various emotional events related to Ekman's emotions. The Corpus has 807 articles from 76 sources. For the above Ekman's emotions, the *ET* terms are identified using synonyms/hyponyms/hypernyms. For instance, {delight, joy, glad, cheerful} are the synonyms/hyponyms/hypernyms that exists for *happy* emotion. The collections of articles are categorized into group such that documents that have common emotions are grouped into the same set. For instance, 4628 EMOT-Mentions are categorized and annotated manually for *Happy* emotion, which is a tedious and vital process. Similarly, 3256 EMOT-Mentions are categorized and annotated manually for *Surprise* emotion etc. This is represented in Table III.

TABLE III
CLASSIFICATION OF EMOT-MENTIONS USING SYNONYMS/ HYPONYMS/ HYPERNYMS

Ekman's Emotions	**Trigger terms**	**EMOT-Mentions**
Happy	25	4628
Surprise	28	3256
Sad	18	5678
Fear	15	1235
Disgust	11	7895
Anger	21	3621

Here we represent the data for *Happy* emotion alone for want of space and clarity. During this process, the EMOT_Mentions that give description about *Happy* emotion are identified are annotated.

TABLE IV
CORPUS STATISTICS FOR '*HAPPY*' EMOTION

Features	'*Happy*' Emotion
Number of EMOT_Mentions (without synonyms)	358
EMOT_Mentions in S^PEM class	135
EMOT_Mentions in C^PEM class	223
Number of EMOT_Mentions (with synonyms)	4628
EMOT_Mentions in S^PEM class	1971
EMOT_Mentions in C^PEM class	2657

Initially, without using synonyms/hyponyms/hypernyms, we considered a small sample set of 358 EMOT_Mentions for *Happy* emotion, to generate annotations. These annotations are collected to evaluate the usefulness of the proposed approach. EMOT_Mentions. Further, these EMOT_Mentions are broken down into EMOT_Phrases. The EMOT_Mentions having single EMOT_Phrase of emotion is classified as S^PEM class. The EMOT_Mentions having multiple EMOT_Phrases with mixed emotions are classified as C^PEM class. The Corpus statistics for *Happy* emotion category is presented in Table IV.

TABLE V
EMOT-MENTION CLASSIFICATION FOR *HAPPY* EMOTION DATASET (WITHOUT USING SYNONYMS)

EMOT-Mention Classification				
Manual Annotation Classification		Hierarchical Rules Classification		Classification Accuracy(%)
EMOT_Mentions for S^PEM class	Patterns Count (%)	EMOT_Mentions for S^PEM class	Patterns Count (%)	
ASPIEM	5.37	***ASPIEM***	4.23	78.77
PSPIEM	5.24	***PSPIEM***	4.20	80.15
ASNIEM	6.15	***ASNIEM***	5.11	83.08
PSNIEM	8.68	***PSNIEM***	7.60	87.57
ASPEM	7.55	***ASPEM***	6.66	88.21
PSPEM	3.85	***PSPEM***	2.80	72.72
ASNEM	6.15	***ASNEM***	5.25	85.36
PSNEM	9.01	***PSNEM***	8.15	90.45
Manual Annotation Classification		Hierarchical Rules Classification		
EMOT_Mentions for C^PEM class	Patterns Count (%)	EMOT_Mentions for C^PEM class	Patterns Count (%)	Classification Accuracy(%)
ALPIEM	14.44	***ALPIEM***	8.22	0.56
PLPIEM	18.85	***PLPIEM***	11.11	0.58
ALNIEM	17.0	***ALNIEM***	12.2	0.71
PLNIEM	15.74	***PLNIEM***	10.76	0.68
ALPEM	20.07	***ALPEM***	12.89	0.64
PLPEM	18.29	***PLPEM***	11.34	0.62
ALNEM	18.01	***ALNEM***	9.78	0.54
PLNEM	17.21	***PLNEM***	10.4	0.60

Initially, we consider a small sample set of 358 EMOT_Mentions to manually annotate the EMOT_Mentions for S^PEM and C^PEM class. This annotation is done by making different groups. The process of annotation is carried out by sixteen groups of undergraduate students based on POS nature and EMOT_Actifiers of sentence using NLP tool. All the classification output, based on annotation, is re-evaluated by a group of research students. Later, CART tool is used which is based on Hierarchical Classification rules to estimate the classification accuracy between classifier and human annotation. As a performance measure we used classification accuracy, which is defined as the ratio of sentences correctly classified by the classifier to class type *n* to the human annotated sentences for the class type *n*. The results are shown for *Happy* emotion in Table V.

It is noticed that the difference between classifier and manual annotation is less, i.e., in the range of 2-3% for the EMOT_Mention classes of S^PEM category. Also, the classification accuracy between Hierarchical classifier and human annotation matches above 72% for S^PEM class. It is noticed that the difference between classifier and manual annotation exist in a wide qrange i.e., in the range of 5-9% for the EMOT_Mention classes of C^PEM category. Also, the classification accuracy between Hierarchical classifier and human annotation matches in the range of 54% to 71% for C^PEM class. There also exist outliers in Ekman's emotions of C^PEM class. It is observed that these outliers are misclassified EMOT_Mentions. This is due to the presence of multiple EMOT-Phrases (E_p) appearing in lengthy EMOT-Mentions set. In such complex EMOT-Mentions the system fails to identify the syntactic context between the EMOT_Phrases which results in unrecognized emotions. This conflicts and misleads the classifier during classification. Thus, the outliers exist 21% for *Happy* emotion category, 26% for *Sad* emotion category and so on. However, there were no outliers in S^PEM class.

Further, the Event_Mentions of C^PEM and S^PEM class is considered and broken into EMOT_Phrases. These EMOT_Phrases are considered for Phrase-level classification. We estimate classification accuracy using manual annotation and fuzzy rule classification. ANFIS model is used as classifier which acts as a Sugeno-type FIS structure for training the data. We consider an EMOT_Mention and identify EMOT_Phrases in them. Later three features such as *ET, ET±1* and *ET±n* in the phrase are given as input and fuzzy rules are applied which generates sixteen phrasal patterns. The sixteen patterns obtained are used to analyze the performance of rules by classifier using k-fold cross validation technique. We initiated the validation process by considering 2-fold cross validation (holdout method) as it consumes less computational time. The sentences are randomized using random generator and chosen as equal sized validation and training dataset. We performed 2-fold cross validation using training set and expects the classifier to predict the output values for the testing dataset, where these output values have no prior appearance. The performance of classification for this iteration is considered in terms of precision and recall. In the next iteration, again the sentences are randomized with different validation and training datasets, cross validation process is repeated and evaluated. Similarly, the sentences are randomized for *n* iterations (*n*=100) and the average classification performance is considered and evaluated. The average results obtained after *n* iterations are good. Here, the variation between training and test datasets is reduced as the iteration is increased.

TABLE VI
EMOT-PHRASE LEVEL CLASSIFICATION FOR *HAPPY* EMOTION DATASET (WITHOUT USING SYNONYMS)

EMOT-Phrase Level Classification				
Manual Annotation Classification		Fuzzy Rule Classification (2-fold Cross Validation)		
E_P Patterns for S^PEM class	Patterns Count (%)	E_P Patterns for S^PEM class	Patterns Count (%)	Classification Accuracy (%)
$ASPIE_P$	15.17	$ASPIE_P$	14.93	0.98
$PSPIE_P$	25.34	$PSPIE_P$	24.2	0.95
$ASNIE_P$	16.11	$ASNIE_P$	15.91	0.98
$PSNIE_P$	8.88	$PSNIE_P$	7.65	0.86
$ASPE_P$	27.15	$ASPE_P$	26.12	0.96
$PSPE_P$	13.35	$PSPE_P$	12.83	0.96
$ASNE_P$	26.25	$ASNE_P$	25.12	0.95
$PSNE_P$	19.11	$PSNE_P$	17.15	0.89
Manual Annotation Classification		Fuzzy Rule Classification (2-fold Cross Validation)		
E_P Patterns for C^PEM class	Patterns Count (%)	E_P Patterns for C^PEM class	Patterns Count (%)	Classification Accuracy (%)
$ALPIE_P$	36.33	$ALPIE_P$	32.92	0.90
$PLPIE_P$	29.85	$PLPIE_P$	24.91	0.83
$ALNIE_P$	17.73	$ALNIE_P$	16.23	0.91
$PLNIE_P$	33.72	$PLNIE_P$	32.25	0.95
$ALPE_P$	48.17	$ALPE_P$	42.89	0.89
$PLPE_P$	45.22	$PLPE_P$	44.34	0.98
$ALNE_P$	22.91	$ALNE_P$	21.33	0.93
$PLNE_P$	43.67	$PLNE_P$	42.14	0.96

TABLE VII
PERFORMANCE OF ANFIS USING 10-FOLD CROSS VALIDATION FOR PHRASE LEVEL CLASSIFICATION

Number of '*Happy*' EMOT_Mentions : 358 (without using synonyms): Number of EMOT_Mentions in C^PEM class: 135 Number of EMOT_Mentions in S^PEM class: 223							
S^PEM class patterns	Prec (%)	Recal l (%)	F1 (%)	C^PEM class patterns	Prec (%)	Recall (%)	F1 (%)
$ASPIE_P$	98.11	93.01	96.23	$ALPIE_P$	87.2	82.34	86.45
$PSPIE_P$	95.02	92.45	93.2	$PLPIE_P$	89.87	86.7	86.04
$ASNIE_P$	98.45	90.02	94.8	$ALNIE_P$	85.44	84.2	84.9
$PSNIE_P$	94.65	95.23	94	$PLNIE_P$	94.9	93.1	93.02
$ASPE_P$	96.01	90.02	93.4	$ALPE_P$	82.07	80.09	81.71
$PSPE_P$	94.76	94.02	94.4	$PLPE_P$	91.01	93.65	92.51
$ASNE_P$	98.11	95.12	97.1	$ALNE_P$	89.06	95.23	90.03
$PSNE_P$	93.01	97.01	95.8	$PLNE_P$	90.31	91.19	90.74

Later, 10-fold cross validation is used to evaluate the performance of rules by dividing the data set into 10 sets and the cross validation is repeated 10 times. Each time, one of the 10 subsets is used as the test set and the other nine subsets are put together to form a training set. The 10 results from the folds are averaged to produce a single estimation. The well-known performance measures such as Precision, Recall and F1-measure are used for evaluation. Precision is defined as the ratio of number of sentences correctly classified by a classifier to a class type *n* to the total number of sentences classified by a system to a class type *n*. Recall is defined as the ratio of number of sentences correctly classified by a classifier to a class type *n* to the total number of human-annotated sentences of class type *n* and F1 measure gives the harmonic measure of Precision and Recall for class type ***n***. The results are shown in Table VII.

It is noticed that the difference between classifier and manual annotation is less at Phrase-level classification of S^PEM category. Also, the classification accuracy between human annotation and fuzzy rule classification matches above 85% for S^PEM class. For C^PEM category also, the difference between classifier and manual annotation is less wherein the classification accuracy occurs in the range of 83% to 96%. The results are well depicted in Table VI.

V. CONCLUSION

The proposed approach identifies emotions based on EMOT_Actifiers and using POS features. The approach considers emotion triggered terms and its co-occurrence terms in the sentence. The sentences are classified at Phrase-level to identify Positive and Negative Orientations. The generated patterns of classification are analyzed and grouped into the Positive emotions and Negative emotions. Later, the intensities are assigned for capturing the degree of emotions that exist in semantic of expression. Further, neural network is used as machine learning tool to learn the patterns of Positive and Negative emotions which captures the psychology of a person. The proposed approach performs is encouraging when compared with other similar approaches.

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