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Enhanced Weight Based Convolutional Neural Network (EWCNN) and Fuzzy Clustering For Semantically Rich Multi-Label Social Emotion Classification

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ABSTRACT: In Recent Years, Social Emotion In Recent Years Acquires Natural Language Processing Researchers' Attention, Because Of Analyzing User-Generated Emotional Documents On The Web. But, These Emotions Has Noisy Instance Mixed And It Is Great Dispute To Acquire The Textual Meaning Of Short Messages. Definition: In General, Large-Scale Datasets Will Have Many Noisy Data, Which Can't Be Used Readily And Also It Is Costly, Because Of Ambiguity Of Various Informal Expressions In User-Generated Comments. It Is Very Tedious One To Recognize The Similar User Documents From The Entire Social Media Text Message. Furthermore, Online Comments Are Characteristically Categorized By A Sparse Feature Space, Which Makes The Respective Emotion Classification Task A Complex One. Methodology: Three Major Contributions Were Done In This Work In Order To Rectify These Problems, They Are: Development Of A Novel Mutation Bat Optimization Based Sparse Encoding (MBO-SC) Which Transforming The Sparse Low-Level Features Into Dense High-Level Features, Was The 1st Contribution, Next Is, An Enhanced Weight Based Convolutional Neural Network (EWCNN) To Target-Specific Layer. It Influences The Semantically EWCNN Classifier To Include Semantic Domain Knowledge Into The Neural Network To Bootstrap Its Inference Power And Interpretability. Fuzzy Clustering Algorithm Is Proposed To Minimize The Similarity Among Two Documents. Uses: It Is Quite Constructive In Recommending Products, Collecting Public Opinions, And Predicting Election Results. Proposed Work Is Distinguished With The Existing Methods, With The Metrics Such As: Precision, Recall, Sensitivity, Specificity, F-Measure And Accuracy. From The Experimental Result It Is Confirmed That The Quality Of Learned Semantic Vectors And The Performance Of Social Emotion Classification Can Be Enhanced By Proposed Models.

INDEX TERMS: Data Mining, Social Media Data, Clustering, Classification, Transfer Learning, Sparse Coding, Social Emotion Classification, Enhanced Weight Based Convolutional Neural Network (EWCNN), Mutation Bat Optimization Based Sparse Encoding (MBO-SC) And Fuzzy Clustering.

I. INTRODUCTION

People's feelings and thoughts, were measured by the key factor called emotions.

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Online social media, like Twitter and Face book, have changed the language of communication. At present, people can communicate facts, opinions, emotions, and emotion intensities on various kinds of topics in short texts. In the natural language processing research field, examining the emotions have got much attention from the researchers. Further, it has various applications in commerce, public health, social welfare, etc. For example: it helps in public health [1,2], public opinion detection about political tendencies [3], brand management [4], and stock market monitoring [5]. Emotion analysis is the task of determining the attitude towards a target or topic. The attitude can be the divergence (positive or negative) or an emotional state like joy, anger, or sadness [6].

Estimating the aggregation of emotional responses shared by different users; such a computational task has been introduced as one of the bench-mark tasks since the "SemEval" conference was held in 2007, was the target of social emotion classification. But, earlier analysis on social emotion classification repeatedly adopted a wordlevel classification technique which doesn't fulfil to effectively distinguish different emotional senses carrying by the same word. The emotion-topic model [7] and three supervised topic models, such as the multi-label supervised topic model, the sentiment latent topic model, and the affective topic model [8, 9] were established to classify social emotions with reference to "topics" which represents a semantically coherent "concept", in order to mention those weaknesses. Further, the same word in different topics may convey different attitudes.

In order to discover the emotions of topics [7], Emotion-Topic Model (ETM) was proposed by the author. The main drawback of this method was: that it treats every training document equally, so the documents that suggest prominent emotions in readers are usually mixed with noisy documents which don't express much affective meaning. Emotion detection is considered as the supervised multi-label classification problem, since every sentence may has one or more emotions from a standard emotion set containing anger, anticipation, disgust, fear, joy, love, optimism, pessimism, sadness, surprise and trust. But, current topic-level emotion classification methods undergo from the data sparsity problem (e.g., the sparse word co-occurrence patterns found in an online textual corpus), and their classification performance is only shown to be suitable over short messages [10].

Lexicon-based methods [11] , graphical model-based methods [12] and linear classifier-based methods [13] , were there in the conventional approaches to emotion detection. Provided with the recent success of deep learning models, different neural network models and advanced attention mechanisms have been proposed for this task and have accomplished highly competitive results on several benchmark datasets [14-15].

The previous approach tends to learn the sentence representation to pay more attention to general sentiment words like good but less attention to the other sentiment-ambiguous words such as shock that are also integral to emotion classification, when enforcing these classification approaches to proposed scenario. Both the sentiment and the emotion-specific words were acquired by the latter approach. Enhancing the performance of multi-label emotion classification with the help of sentiment classification was the main focus of our proposed work. In order to classify the sentence representation into two different feature spaces, which are expected to correspondingly capture the general sentiment words and the other important emotion-specific words via a dual mechanism, the author proposed the new machine learning algorithm. Transforming sparse low-level features to dense high-level features by Mutation Bat Optimization based Sparse Encoding (MBO-SC), their effectiveness on emotion classification requires further investigation, was the basic contribution of this work. Reducing the similarity between two documents was done by Fuzzy Clustering algorithm. Unsupervised teaching models was leveraged to include the semantic domain knowledge into the neural network to bootstrap its inference power and interpretability, was performed by the novel model of semantically rich EWCNN.

II. LITERATURE REVIEW

Joint Binary Neural Network (JBNN) was proposed by He et al [14] in order to state these drawbacks: the depiction of the text is fed to a set of logistic functions rather than a softmax function, and the multiple binary classifications are carried out synchronously in one neural network framework. Furthermore, the relations among labels are captured through training on Joint Binary Cross Entropy (JBCE) loss. To fulfil the meet multi-label emotion classification, the author further proposed to include the prior label relations into the JBCE loss. From the experimental result it is confirmed that the JBNN model performs considerably better when compared with the state-of-the-art multi-label emotion classification methods, in both classification performance and computational efficiency.

An attention-based classifier was proposed by Kim et al [15], for estimating the multiple emotions of a given sentence. Human's two-step procedure of sentence understanding was imitated by this model and it further effectively symbolizes and classifies sentences. The model's performance was further enhanced by emoji-to-meaning preprocessing and extra lexicon utilization. Further it was trained and computed the model with data given by SemEval-2018 task 1-5, each sentence of which has several labels among 11 given emotions. Attention-based classifier accomplishes 5th/1st rank in English/Spanish correspondingly. This method doesn't consider a latent relation of emotions in the dataset. With the help of using Plutchik's wheel of emotions model and a rule-based approach for emotion detection in text makes it a good framework for emotion classification on social media and this was argued by Tromp and Pechenizkiy [16]. A detailed description was given on how to determine the rule-based patterns for Plutchik's wheel emotion detection, how to learn them from the annotated social media and how to enforce them for classifying emotions in the previously unseen texts. The described framework is promising and that it advances the current state-of-the-art in emotion detection, which was confirmed from the experimental result. Proposed work executes better when compared with other languages from other groups, for instance: Slavic languages or Asian languages. It is also plan to explore methods to recognize the patterns in an automated fashion instead through a manual labelling process.

The representation of tweets using a novel set of feature was given by Jabreel et al [17], which, in turn, incorporates the bag of negated words and the information given by seven lexicons. According to the Support Vector Machine, the polarity of tweets was determined by a classifier. On the standard tweet sets with the help of the SemEval 2015 competition, this system has been computed, so the obtaining results that, in most cases, beats those of the state-of-the-art sentiment analysis systems. Further it gives less attention to the other sentiment-ambiguous words like shock.

Topic-Level Maximum Entropy (TME) model for social emotion classification over short text was given by Rao et al [18]. This model establishes the topic-level features by modelling latent topics, multiple emotion labels, and valence scored by several readers jointly. By mapping the features to the concept space, we can rectify the over fitting problem in the maximum entropy principle. The effectiveness of TME on social emotion classification over sparse words was evaluated by this experiment which is performed on the real-world short documents. But data sparse problem can't be rectified by this approach. The classification of social emotions on varied-scale data sets was concerned by Li et al [19]. Unlike the traditional models which weight training documents equally, the idea of emotional entropy was proposed to compute the weight and deal with the issue of noisy documents. We make use of the topic assignment for distinguishing the different emotional senses of the same word. An experimental evaluation through various data sets computes the effectiveness of the proposed social emotion classification model. A generalized index of document importance was developed by enhancing the emotional entropy. On reducing the impact of noisy instances and learning a better representation of sentences, Li et al [20] focused at. An "emotional concentration" indicator was brought-in by the former, which was derived from emotional ratings to weight documents. Phrase-level Convolutional Neural Network (PCNN) was proposed for the latter one, which makes use of the two cascading convolutional layers to model the word-phrase relation and the phrase-sentence relation. This model considers the continuous tokens as phrases according to an assumption that neighboring words are very probable to have internal relations, and semantic feature vectors were created according to the phrase representation.

Also a Bayesian-based model was proposed to learn document-level semantic features. Experiments on two real-world datasets represent that the quality of learned semantic vectors and the performance of social emotion classification can be enhanced by models. The training of PCNN takes much time on large datasets.

A development of a novel deep learning-based system was proposed by Jabreel and Moreno [21], which mentions the multiple emotion classification problems in Twitter. Proposed a novel method to change it to a binary classification problem and develop a deep learning approach to rectify the transformed problem. Proposed system beats the state-of-the-art systems, accomplishing an accuracy score of 0.59 on the challenging SemEval2018 Task 1:E-cmulti-label emotion classification problem. Deep learning-based system doesn't model the relationships among the phrases and the labels.

III. PROPOSED METHODOLOGY

The performance of multi-label emotion classification was enhanced through sentiment classification and this was the main target of this proposed work. Furthermore, sparse feature space was characterized by online comments, which establishes the respective emotion classification task very difficult. Otherwise, a novel Mutation Bat Optimization based Sparse Encoding (MBO-SC) which transforming the sparse low-level features into dense high-level features, was the 1st contribution, next is, an Enhanced Weight based Convolutional Neural Network (EWCNN) to target-specific layer. It influences the semantically EWCNN classifier to include semantic domain knowledge into the neural network to bootstrap its inference power and interpretability. And it classifies the sentence representation into two different feature spaces, which are expected to respectively capture the general sentiment words and the other important emotion-specific words via a dual mechanism. Final Fuzzy Clustering algorithm is proposed to minimize the similarity among two documents. The overall representation of the proposed work is shown in the figure 1.

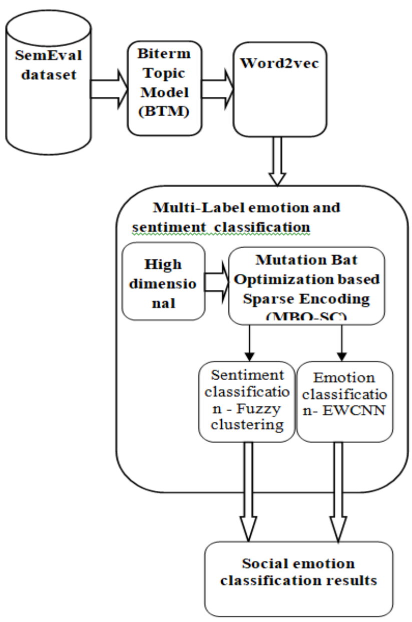


Figure 1. Flow Diagram Of The

IV. PROPOSED WORK

4.1. Biterm Topic Model (BTM)

The Biterm Topic Model (BTM) [22], a probabilistic generative model, which acquires the generation of word co-occurrence patterns in short messages and it, further, extends the conventional word boundary by including the virtual text window of comprising n words. Specifically, if the window size is assumed two, two words (i.e., a biterm, which is an unordered word pair co-occurring in a document) is treated as an individual syntactical unit for predicting the generation probability, and it shares the same topic drawn from the entire corpus. The co-occurrence of words was captured by BTM explicitly, for improving the topic learning, and it improves the problem of sparsity at the document level.

4.2. Word2vec

Google gives the Word2vec as an open source tool, which indicates the words as vectors and extracts the associations between words in a textual corpus and it is so called as word embeddings [23]. With the help of unsupervised learning, it generates meaningful word embedding representation and further it will be trained to extract the meaningful word embedding representation. Specifically, every word will be mapped to a high dimensional word embedding vector, and word embedding vectors with similar semantic meanings appear in a cluster. Otherwise, it is termed as the word embedding vectors which indicates the semantic relations between words which can be leveraged to improve the text classification tasks [24].

4.3. Sparse coding

High order features will be generated by sparse encoding methods in a better way when compared with their non-sparse counterparts. The merits of utilizing the sparse encoding methods are that classifiers tend to perform better given a low dimensional feature space [25] [26]. In the biology field, the similar observations can be acquired, where the living creatures tend to favour sparse representations. The implication of the sparse encoding variant of the Latent Semantic Machine (LSM) establishes the entire network, more robust to the nose which is established by teaching models for the suggested hybrid neural networks. Figure 2 gives the transfer learning approach operationalized by the LSM that are associated with unsupervised teaching models. Every LSM is composed of two layers which accept raw features (i.e., input layer) and transforming them to semantic features of higher-order (i.e., hidden layer). The semantics of the input layer of the LSM is known as "terms", and the input value to the neurons of this layer indicates "term weights". Otherwise, the hidden layer of the LSM captures high-order semantics like "topics", and the numerical outputs of the neurons pertaining to this layer capture the topic distribution which describes the semantics of the underlying corpus.

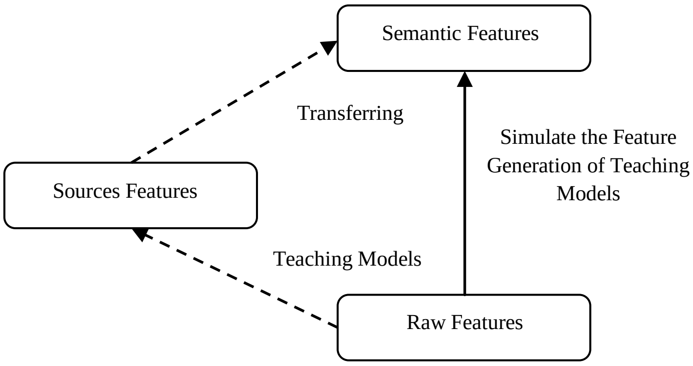


Figure 2. Lsm- Transfer Learning Initiated By Teaching Models

The KL divergence between the distribution of the semantic features were established for a regularized transfer learning of the LSM, with the help of the teaching model and the approximated distribution learnt by the LSM must be minimized (Eq. (1)), and further, the sparsity of the hidden units of the LSM should be regulated. A LSM mimic's feature generation by acquiring the source features were created by unsupervised teaching techniques. LSM learns a mapping function $f(v_d|w,b)$with the intension that$f(v_d|w,b)$ techniques φ_d, here w,b indicates the network's weight terms and b represents the network parameters, and $\varphi_d$denote the source features of a document d, which were established by a teaching model. A Softmax function helps to beat the LSM, with the target of generating normalized variables. Specifically, for establishing the transfer learning function, Kullback-Leibler Divergence (KLD) was enforced in this manner:

$$\mathrm{L}(\varphi,f) = \varphi \log\frac{\varphi}{f} + (1-\varphi)\log\frac{(1-\varphi)}{(1-f)} \quad (1)$$

Here $\varphi$is the source features generated by an unsupervised teaching technique, and f is the approximate distribution $f(v_d|w,b)$learned by the LSM. KL divergence is a (non-symmetric) measure of the variance between the two probability distributions [22]. It is regularly a non-negative value, which is zero when the two distributions are alike. Based on Equation (1), the transfer learning function was reported as the KL divergence among the distribution of the source features which has been created by the teaching model as well as the approximate distribution of these features learned by the LSM. The distributions of source features generated by the teaching model are assumed as constants, and just the last term that function as the network parameters is related to optimization while we focus on calculating the estimated expectation. Hence, maximizing the log-likelihood transmits to minimizing the KL divergence in addition to its gradient in this manner:

$$\frac{\partial L(\varphi,f)}{\partial w_{ij}} = -(\varphi_j - f_j((v|w,b)).v_i \quad (2)$$

$$\frac{\partial L(\varphi,f)}{\partial b_{ij}} = -(\varphi_j - f_j((v|w,b)) \quad (3)$$

In order to enhance the entire performance of the hybrid neural network because not all semantic features (e.g., topics) produced by a teaching model is appropriate in terms of the target task (e.g., social emotion classification); so, we make use of the sparse encoding for LSM. Hence, some of the transferred features should be filtered out through proposed sparse encoding method.

The sources features of a specific dimensionality have been generated for developing the appropriate dimensionality with the help of a teaching model were enforced to proceed with the target classification task (e.g., social emotion classification). By systematically trying out various dimensionality values of source features, and monitoring the respective performance of the classification task according to the training set, which can develop the appropriate dimensionality of the source features.

Mutation Bat Optimization (MBO)

Bat Algorithm [27-28] functions according to the echolocation capability of micro bats which has been guided by their foraging behaviour. In BA, the position of a bat was indicated with the help of the number of features in the documents of Semeval dataset $\{d_{1j}, d_{2j}, \ldots, d_{nj}\}$ be a set of documents which has been utilized for sparse coding issue in the multi-label emotion classification. The position of the web documents from SemEval dataset the i^{th} bat can be formulated as $x = (x_{1j}, \ldots x_{nj})$. The fitness function fit_i respective to the classification accuracy of the multi-label emotion classification with the point of the bat locates [29]. In this work fitness function is nothing but: exactly classified documents from one class to another document with same class.

a) Initiation of bats

Bats don't know the location of web documents initially. So, they will create a randomly distributed population P of N solutions, where 'i' represent the number of documents in the Semeval dataset where i=1,..n. Every sparse coding result can be generated within the search space as follows:

$$\mathrm{fe_{ij}} = \mathrm{fe_{min}} + \mathrm{rand}(0,1)(\mathrm{fe_{max}} - \mathrm{fe_{min}}) \quad (4)$$

Where $\mathrm{i} = 1,\ldots \mathrm{n}$ and$\mathrm{j} = 1,\ldots \mathrm{D}$, $\mathrm{f_{max}}$ & $\mathrm{f_{min}}$ indicate the upper and lower bounds of the dimensionality reduced features in documents i and $\mathrm{j^{th}}$ correspondingly and $\mathrm{rand}(0,1)$ is a uniformly distributed value with the range [0,1].

b) Generation of New Solutions

The new dimensionality reduced features solution was changed by bats and it works according to the documents of the current positions of the bat and the best reduced sparse coding features by the performance of classification task based on the training set.

By adjusting the flying directions the bats will move with the help of their own and other swarm members' best classification accuracy, for recognizing the dimensionality reduced feature. Here, for every position fe_i, a new key was devised as follows:

$$fre_i = fre_{min} + \beta(fre_{max} - fre_{min}) \quad (5)$$

$$ve_i^t = ve_i^{t-1} + (fe_i^t - fe^*)fr_i \quad (6)$$

$$fe_i^t = fe_i^{t-1} + ve_i^t \quad (7)$$

where 'i' indicates each users in the cloud computing environment, $i = 1, \dots N$, and t indicates the t^{th} iteration. fe_i^t and ve_i^t are the position and velocity components of the i^{th} document in the Semeval dataset at the t^{th} iteration. fre_i represented the pulse frequency that affects the velocity of the i^{th} document, fre_{max} and fre_{min} indicates the maximum and minimum of fre_i . β is a random number between [0,1][27] .

The accuracy of the multi-label emotion classification will be enhanced when β is computed via the use of the mutation parameter. From the random value, two or three more choices of the values were combined together, further the mutated value of random number which provides the highest classification is assumed as the sparse reduced feature results. From its initial state, mutations alters one or more random values in a β. The solution modifies entirely from the previous best random distribution result for sparse reduction in SemEval Dataset for emotion and sentiment classification. fe^* is the best position found from the whole SemEval Dataset for sparse reduction in SC.

c) Local Search

The local search is invoked by bats' random walk, once after the new reduced dimensionality features were chosen from MBO and sparse coding. Choose fe_{old}^i from the SemEval and generate a new feature fe_{new}^i, if the pulse emission rate $er_i \in [0,1]$ of the i^{th} document is smaller than a random number, and they were expressed as:

$$fe_{new}^i = fe_{old}^i + \varepsilon A^t \quad (8)$$

where fe_{old}^i indicates a solution which is selected in current SemEval for emotion classification and ε is a random vector drawn from a uniform distribution. A^t is the average loudness of all samples at iteration t .

d) Solutions, Loudness, and Pulse Emission Rate Updating

If a random number is bigger when compared with the loudness A^t and $fit(fe_{new}^i) < fit(fe_i)$, they will accept the newly dimensionality reduced sparse coding features fe_{new}^i. Simultaneously, the loudness A^t will be reduced while its pulse emission r_i is increased as follows[29]:

$$A_i^{t+1} = \alpha A_i^t \quad (9)$$

$$r_i^{t+1} = r_i^0(1 - e^{-\gamma t}) \quad (10)$$

where α and γ are constants. The initial loudness A^0 and initial pulse emission rate r_i^0 are randomly generated numbers in the range of [1,2] and [0,1], correspondingly.

Algorithm 1. MBO with Sparse Coding

Input: Input documents of SemEval dataset $\{d_{1j}, d_{2j}, \dots, d_{nj}\}$

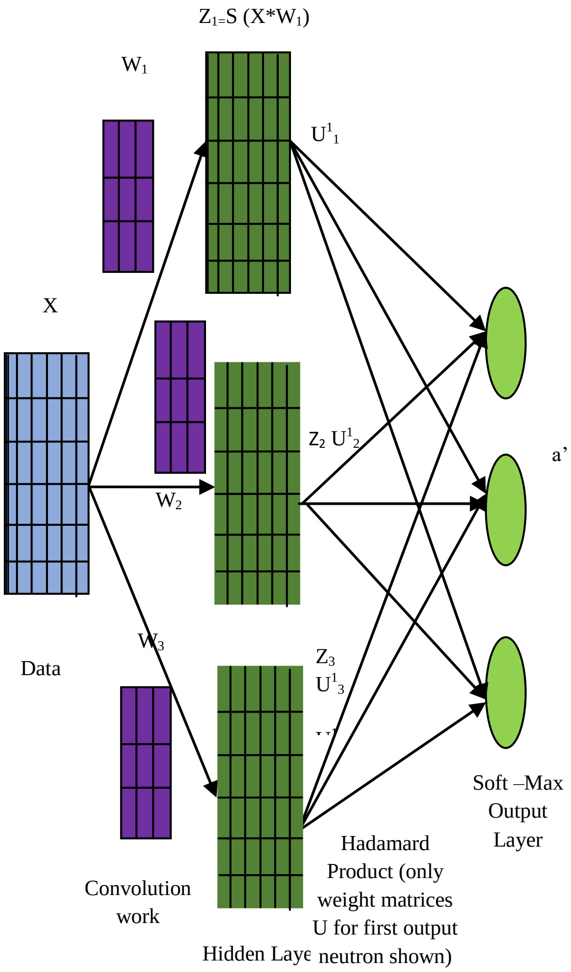
Output: dimensionality reduced features

1. Set iter=1
2. Initialize the Semeval dataset position and velocity of each Semeval dataset in the documents
3. Evaluate the fitness value of the classification accuracy
4. While iter ≤ iter_max do
   - 4.1. Find the suitable dimensionality reduced features
   - 4.2. Generate new solutions using Eq. (5) ~Eq. (7) // As a result, a new key was devised
   - 4.3. if rand(0,1) > r_i
     - i) Generate a new reduced feature vector with the selected solution fe^* using Eq. (8) //Local Search Process
     - ii) Until it reaches all Semeval dataset
     - iii) Break
   - 4.4. End if
   - 4.5. if rand (0,1)<A_i and $fit(fe_{new}^i) < fit(fe_i)$ Update the new reduced feature vector, loudness and pulse emission rate by Eq. (9-10) // Solutions, Loudness, and Pulse Emission Rate Updating
   - 4.6. end if
5. end while
6. return dimensionality reduced features

4.4. Enhanced Weight based Convolutional Neural Network (EWCNN)

This phase novel model of semantically rich Enhanced Weight based Convolutional Neural Network (EWCNN) is proposed which influences the unsupervised models to include the semantic domain knowledge into the neural network to bootstrap its inference power and interpretability. Here resort to sentiment classification was assumed to transfer learning scenario, because of the limited number of annotated data for multi-label emotion classification. Let $D^s = \{x^m, y^m\}_{m=1}^M$ be another set of labeled sentences for sentiment classification, where y(m) is the ground-truth label indicating whether the mth sentence is positive, negative or neutral.

For emotion classification, Enhanced Weight based Convolutional Neural Network (EWCNN) algorithm is proposed in this work. Figure 3 reveals the architecture of a CNN with a single hidden convolutional layer and three convolutional masks. Without any constraints, the two sparse reduced feature spaces may both be liable to pay more concentration to frequently occurring and significant sentiment words like great and happy, but less to those hardly ever occurring but crucial emotion words like anxiety and panic. Hence, to encourage the two feature spaces focus on sentiment words and emotion-specific words correspondingly, propose through the attention weights are computed from the shared layer as extra inputs for target-specific layer.



Solutions, Loudness, and Pulse Emission Rate Updating
Figure 3. Enhanced Weight Based Convolutional Neural Network (Ewcnn)

The diagram reveals a EWCNN with just one hidden convolutional layer [30]. The input samples X convolves with the 3 masks W_1, W_2, and W_3. The resulting emotion classifications via the hidden neurons were executed with logistic sigmoid activations [31]. Then the EWCNN measures the element-wise Hadamard products among the hidden neuron activation matrices Z_1, Z_2, and Z_3 with weight matrices U_j^k where j = 1, 2, 3 and k = 1, 2, 3. The output neurons have softmax activations that determine a discrete Gibbs probability density function. Let X indicates the input two-dimensional data of size $M_X \times N_X$ where M_X and N_X are positive integers. The 2D filters W_1,.. , W_J are every of size $M_W \times N_W$. Then the convolution of X with the filter W_j gives the matrix

$$C_j = X * W_j \quad (11)$$

where ∗ represents 2D convolution. The 2D data matrix C_j has size $(M_X + M_W - 1) \times (N_X + N_Y - 1)$ with (m, n)th entry

$$C_j(m,n) = \sum_{a=1}^{M_W} \sum_{b=1}^{N_W} X(a-m, b-n) W_j(a,b) \quad (12)$$

Pad X with zeros to determines it at all points in the above double sum. Then pass the J matrices C_1, . . . , C_J element-wise through logistic sigmoid functions s to give the hidden-neuron activations Z_j:

$$Z_j(m,n) = s\left(C_j(m,n)\right) = \frac{1}{1 + \exp\left(-C_j(m,n)\right)} \quad (13)$$

Suppose the network has K output neurons. A $(M_X + M_W - 1) \times (N_X + N_Y - 1)$ weight matrix U_j^k multiplies the jth hidden neuron matrix Z_j element-wise. The softmax or Gibbs activation at k of the kth output neuron is the ratio

$$a_k^t = \frac{\exp\left(\sum_{j=1}^{J} e^T Z_j \odot U_j^k e\right)}{\sum_{k_1=1}^{K} \exp\left(\sum_{j=1}^{J} e^T Z_j \odot U_j^{k_1} e\right)} \quad (14)$$

Where ⊙ represents the element-wise Hadamard product among two matrices, e is a vector of all 1s of length $(M_X + M_W - 1)(N_X + N_W - 1)$. The JK matrices U_j^k (j = 1, . . . , J and k = 1, . . . , K) are the weights of the connections among the hidden neurons and the output neurons.

Another similarity loss has been brought-in to clearly implement the variations among the two attention weights of the semantic and emotion is measured through the use of the mean value between the documents. The mean values among the dataset were measured to discriminate the exact variations among the sentiment samples. Need to reduce the similarity between emotion samples, for classifying the sentiment samples efficiently.

4.5. Fuzzy clustering

Here, the dataset is indicated by Da, where Da={da_1, da_2, da_3, …… da_n}, specify n points in 2-dimensional space of the sentiment dataset. Centroids of clusters are denoted by ce_k and c is the total number of clusters present in the dataset, k helps to represent the cluster. Hence, value of k is in the range [1,c]. It functions on the assumption that numbers of clusters 'c' are known for the given dataset and reduces the objective function (J_{FCM}), given as:

$$J_{FCM} = \sum_{k=1}^{c}\sum_{i=1}^{n} \mu_{ik}^{m} dis_{ik}^{2} \quad (15)$$

Where μ_{ik} is the membership of datapoint 'da_i' in cluster 'k' and $dis_{ik} = ||da_i - ce_k||$ is the Euclidean distance between 'da_i' and cluster center ce_k and membership μ_{ik} fulfills the following relationship:

$$\sum_{k=1}^{c} \mu_{ik} = 1, i = 1, \dots n \quad (16)$$

and 'm' is a constant value known as the fuzzifier (or fuzziness index) as it manages the fuzziness of the resulting clusters. In our execution m is considered as two. Membership of every point is updated with the help of the following equation:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{dis_{ki}}{dis_{ji}}\right)^{\frac{2}{m-1}}}, \forall\, k, i \quad (17)$$

here k is an integer in range [1,c] and i is an integer in range [1,n] and

$$ce_k = \frac{\sum_{i=1}^{n}(\mu_{ik}^{m} da_i)}{\sum_{i=1}^{n}(\mu_{ik}^{m})} \quad (18)$$

Two different feature spaces, which are expected to respectively capture the general sentiment words and the other significant emotion-specific words through a clustering and classification metrics.

The overall Step by Step Procedure of EWCNN is given as follows:

Step 1: Initialize the input SemEval dataset for the further classification process

Step 2: Follow the BTM and word2vec for pre-processing step to produce the high dimensional data and for further text classification task

Step 3: LSM method is applied on high dimensional data by sparse coding to develop the appropriate dimensionality of the source features

Step 4: Further to reduce the feature dimension the MBO with Sparse Coding is applied as the feature selection model

Step 5: The sentiment classification is finally done using the proposed EWCNN with class label of the sentence as positive, negative or neutral.

V. RESULTS AND DISCUSSION

Datasets and experimental settings were explained here and then experimental results involve the comparative analysis among experimental method and other baseline methods. For English, we need to enforce a widely used Twitter dataset from SemEval 2016 Task 4A [32] as source sentiment classification task. Task A comprises of 3 sentiment classes — positive, neutral and negative. For target emotion classification task, we utilize the Twitter dataset recently released by SemEval 2018 Task 1C [33] which contain 11 emotions. The word embedding size d is set to be 300 for E1. Classify the tweet as 'neutral or no emotion' or as one, or more, of eleven given emotions that best represent the mental state of the tweeter:

- anger (also includes annoyance and rage) can be inferred
- anticipation (also includes interest and vigilance) can be inferred
- disgust (also includes disinterest, dislike and loathing) can be inferred
- fear (also includes apprehension, anxiety, concern, and terror) can be inferred
- joy (also includes serenity and ecstasy) can be inferred
- love (also includes affection) can be inferred
- optimism (also includes hopefulness and confidence) can be inferred
- pessimism (also includes cynicism and lack of confidence) can be inferred
- sadness (also includes pensiveness and grief) can be inferred
- suprise (also includes distraction and amazement) can be inferred
- trust (also includes acceptance, liking, and admiration) can be inferred

Here, we utilize SemEval-18 Task 1C and metrics like accuracy, precision, recall, sensitivity, specificity and f-measure. Precision is the percentage of the classifier success among entire tweets were classified like belong to a class, recall is the percentage of the classifier success among entire tweets belong to a class , and F-measure is an harmonic among precision and recall and is closer to smaller value of them. Specificity (also called the true negative rate) computes the proportion of actual negatives that are correctly recognized as Negative.

$$Precision = \frac{TP}{TP + FP} \quad (19)$$

$$Recall = \frac{TP}{TP + FN} \quad (20)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (21)$$

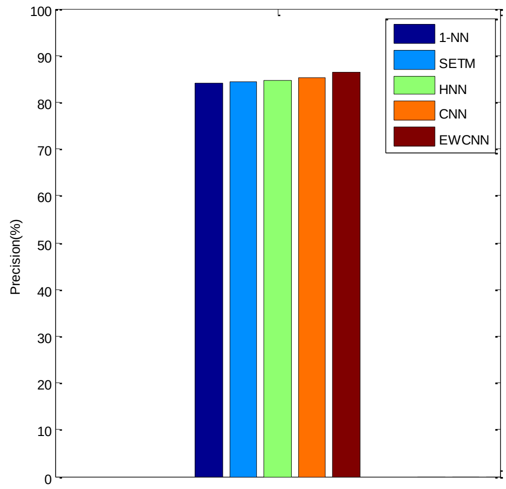
$$F - measure = 2\frac{Precision * Recall}{Precision + Recall} \quad (22)$$

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \quad (23)$$

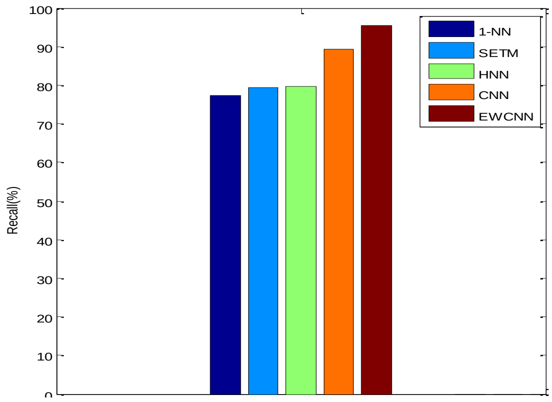
The final measure is accuracy that points to how well a provided classifier works in classifying the document. The results of the proposed EWCNN classifier are measured with Hybrid Neural Networks (HNN) [35], Semantic Emotion Topic Model (SETM) [34] , CNN and 1-NN. Table 1 shows the overall performance comparison results of the methods with respect to various metrics.

TABLE 1. METRICS RESULTS COMPARISON VS. MULTI-LABEL EMOTION CLASSIFICATION METHODS

Metrics	Methods				
	1-NN	SETM	HNN	CNN	EWCNN
Precision (%)	84.21	84.24	84.56	85.23	86.2806
Recall (%)	77.29	79.28	79.68	89.24	95.3712
F-measure (%)	87.09	87.71	87.27	89.33	90.1873
Specificity (%)	81.35	86.56	86.82	90.43	94.9697
Accuracy (%)	80.9	82.4	82.5	84.7	94.9



(a) Precision results comparison vs. methods



(b) Recall results comparison vs. methods

figure 4. Precision And Recall Results Comparison Of Multi-Label Emotion Classification Methods

Figure 4 reveals the performance comparison results of the proposed EWCNN classifier with four classifiers like CNN, HNN, SETM and 1-NN. The results were distinguished with respect to precision and recall metrics are shown in the figure 4(a) and figure 4(b). The results shows that the proposed EWCNN classifier gives higher precision results of 86.2806%, when compared with the other methods such as 84.21%, 84.24%, 84.56%, 85.23% for 1-NN, SETM , HNN, and CNN methods respectively. Since the proposed work sentiment and emotion classification is performed independently through classification and clustering methods.

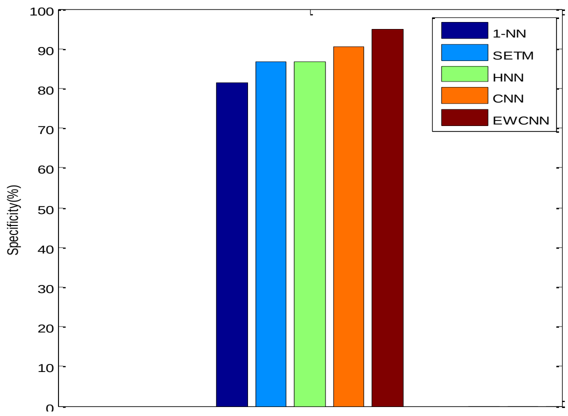


Figure 5. Specificity Comparison Of Multi-Label Emotion Classification Methods

Figure 5 discloses the performance comparison results of the sensitivity comparison metrics to five classification methods. The proposed EWCNN classifier was distinguished with four classifiers like CNN, HNN, SETM and 1-NN. The proposed EWCNN classifier provides higher results of 94.96%, whereas other classifiers such as like CNN, HNN, SETM and 1-NN gives only 90.43%, 86.82%, 86.56% and 81.35% respectively. Since the proposed work, higher dimensional vector is rectified by SC with optimization method.

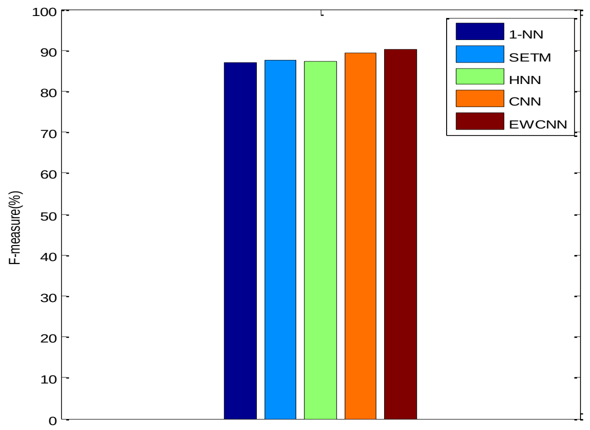


Figure 6. F-Measure Comparison Of Multi-Label Emotion Classification Methods

In the figure 6, the F-measure comparison results of the five classification methods are shown clearly. Those methods are CNN, HNN, SETM, 1-NN and proposed EWCNN classifier. The results discloses that the proposed EWCNN classifier provides higher f-measure results of 90.18%, whereas other existing methods such as CNN, HNN, SETM, 1-NN gives of 89.33%, 87.27%, 87.71% and 87.09% respectively. Since the proposed work, higher dimensional vector is rectified by SC with optimization method.

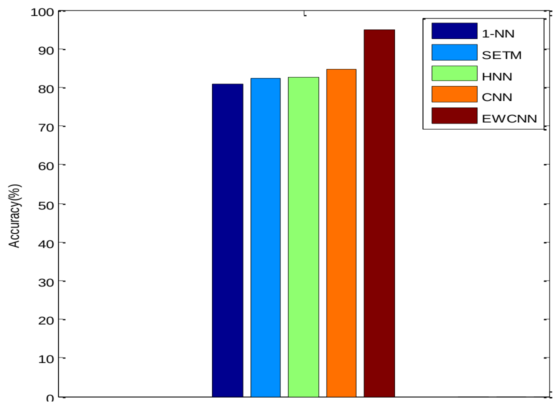


Figure 7. Accuracy Comparison Of Multi-Label Emotion Classification Methods

In the figure 7, the accuracy results comparison of the five classification methods. The results discloses that the proposed EWCNN classifier provides higher accuracy results of 94.90%, whereas other existing methods such as CNN, HNN, SETM, and **1-NN** gives of 84.70%, 82.50%, 82.40% and 80.90% respectively. Since the proposed work, higher dimensional vector is rectified by SC with optimization method.

VI. CONCLUSION AND FUTURE WORK

In order to influence the sentiment classification, the author proposed the Enhanced Weight based Convolutional Neural Network (EWCNN) and Fuzzy Clustering algorithm for enhancing the performance of multi-label emotion classification. A novel Mutation Bat Optimization based Sparse Encoding (MBO-SC) is proposed for feature selection and its outcome provided as input to EWCNN classifier to precede the target classification task. Specifically, the computational models of Latent Semantic Machines (LSMs) were sponsored to include the semantic features into the proposed EWCNN classifier to enhance the classification performance and improve the interpretability of these networks. Thus the proposed methodology produces semantically rich features which can capture various emotion contexts in better way, and hence attributes to enhance the performance of social emotion classification with high accuracy rate of 94.90%. The experiments results reveal that the proposed EWCNN classifiers are effective, and significantly beat to other state-of-the-art systems in multi-label social emotion classification, according to the social media datasets. As from the results, it is well known that the proposed method works better for the emotion classification than the CNN, HNN, SETM, and 1-NN schemes. Future work plans to program the new algorithm for computing the semantic gap among the source features produced by a teaching model and the characteristics of a target task before sparse encoding was enforced to transfer learning.

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