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Survey on Emotion Classification using Deep Learning Algorithms

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ABSTRACT: Deep learning methodologies for analysing the physiological signals in multiple modalities via hierarchical architectures for human emotion recognition have recently gained popularity. Deep learning for emotion classification was used in much of the state-of-the-arts of human emotion recognition. Deep learning, on the other hand, is most useful for extracting deep features.Therefore, in this research, we applied unsupervised deep belief network (DBN) for depth level feature extraction from fused observations of Electro-Dermal Activity (EDA), Photoplethysmogram (PPG) and Zygomaticus Electromyography (zEMG) sensors signals. Afterwards, the DBN produced features are combined with statistical features of EDA, PPG and zEMG to prepare a feature-fusion vector. The prepared feature vector is then used to classify five basic emotions namely Happy, Relaxed, Disgust, Sad and Neutral. As the emotion classes are not linearly separable from the feature-fusion vector, the Fine Gaussian Support Vector Machine (FGSVM) is used with radial basis function kernel for non-linear classification of human emotions. Our experiments on a public multimodal physiological signal dataset show that the DBN, and FGSVM based model significantly increases the accuracy of emotion recognition rate as compared to the existing state-of-the-art emotion classification techniques.

KEYWORDS: Emotion recognition, Physiological signals, Fusion model, Deep belief network, Fine Gaussian support vector machine

I. LITERATURE SURVEY

Leveraging Unlabeled Data for Emotion Recognition with Enhanced Collaborative SemiSupervised Learning
Zixing Zhang[8] proposed that the classifier should first train data and recognise the unlabelled data with confident samples selected through entropy in the presence of a small group of data labelled and a large number of unlabeled data (Semisupervised learning). The same number of samples are permitted for each iteration per class. The unlabeled data is then recognised and trained by labelled data which is called self-learning. After a model is self-learned, the classificator, namely SVM and RNN, is taught to learn strength and avoid weakness.Co-training is the process (Collaborative semisupervised learning). The fusion is made with the recognised trustful information after training for each iteration.

Grey Wolf optimization-based feature selection and classification for facial emotion recognition
Ninupreetha Nirmala sreedharan[4] proposed that the given input pictures were first pre-processed and the features extracted from the face with the aid of a function detection algorithm, namely the transforming of the scale invariant feature. The extracted features are then transmitted through the neural network for grey wolf optimisation and classified as required emotional types. Using the viola jones face detector algorithm, the test image is entered into the system's required facial features. The features chosen are compared to the trained features extracted.

Facial Expression Recognition Based on Cognitive and Mapped Binary Patterns
Chao qi[3] proposed a system of recognising facial expression in two steps. Firstly, the extraction of characteristics and the classification of emotions. Cohn-Kanade Dataset, with 150 images, is the experimental dataset used here. The face contours are removed using the local LBP operator (Local Binary Pattern). A pseudo-3D model is then

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generated in six sub-regions for the facial area. In the process of feature extraction and classification, these areas and global images will support the vector machines and softmax with two models.

Emotion recognition from facial expressions using hybrid feature descriptors

Tehminakalsum[8] suggested a system divided into training and tests for detecting emotions. The necessary features are extracted during training from the face and a codebook is built on these facial features. A codebook is a collection of facial features that are necessary. The coding book is built using a spatial function bag (SBoFs) and spatial invariant transformation feature (SSIFT). The built codebook set is then inserted into the classification classifier. The image is pre-processed and the face characteristics are extracted during testing.

Predicting Personalized Image Emotion Perceptions in Social Networks

Sichengzhao[5] has suggested predicting an emotional perception personalised to each viewers' images. IAPS dataset, abstract dataset and emotion dataset are the data sets for testing. This data set includes images depicting complex scenes such as portraits, animals, landscapes etc. 200 images were selected with associated titles, marks and descriptions from each emotional category. The pictures taken from social networks detected sudden emotional changes.

Facial expression recognition using weighted mixture deep neural network based on doublechannel facial images

Biao Yang [2] proposed the detection of different image categories by the use of the neural network convolution. This dataset is used by Cohn-Kanada Dataset, JAFFE and Oulu-CASIA. The dataset is used for this purpose. This undergoes a pre- and amplification process of data. Then calculation of the local binary pattern.

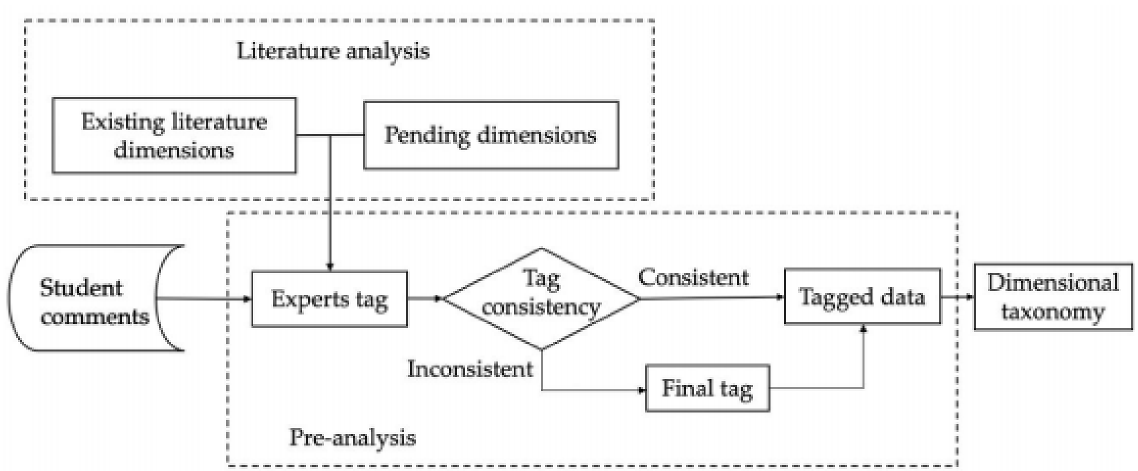

Figure 1. Aspect-oriented academic emotion classification system

Automatic facial expression recognition using features of salient facial patches

S L Happy [7] has proposed to use the salient facial features that include mainly eyes, nose, lips and eyebrow that are very important to the making of a particular emotion to detect the type of emotion of the human face. The face images are preprocessed and the facial characteristics are derived from the respective ROIs.

Our project aims at examining face emotions using CNN in real time. This type of profound learning technique gives us the solution after significant training [2] for many problems in the recognition of facial emotions. The main benefit of the CNN is that the physically based models and/or other preprocessing techniques are completely removed or significantly reduced by allowing 'end-to-end' learning from the input source [3].

Automatic recognition and the study of the facial emotional condition is an important way to identify, study and protect individuals who are vulnerable, such as patients with mental difficulties, individuals with critical mental weights and children with less self-control[4].

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Although we used our project's data set for Fer2013, it was a bit difficult to distinguish emotions between fear, surprise, and disgust, therefore we sorted it in a single group of 5 emotions called surprise that included happiness, sadness, anger, and neutrality. The Fer2013 dataset was provided by Kaggle, which represents spontaneous facial expressions from the real world under all difficult circumstances such as different lighting conditions, different head motions and facial variances due to their ethnicity, age, gender, face hair and glass.

The accurate understanding of emotional facial expressions is one of the determinants of interpersonal relationship quality. The more one correctly reads another's emotions, the more one is involved. Some social interaction problems may be related to difficulty recognising facial expressions in some psychopathological disorders (2). In various clinical populations, such deficits have been demonstrated. However, the studies have so far produced differing findings with regard to facial expressions.The objective of this article is to examine the subject of emotion (3), faces from ancient times, to highlight the strengths and weaknesses of the related studies, to compare the results and to take this novel issue to the attention of Turkey.
The first significant physiological emotion theory was proposed in 1884 by William James. James maintained that emotion is rooted in the body. In his view, we first perceive that the object then the body reacts and ultimately there is emotional excitement (Kowalski and Westen 2005 p347). We have a ponded heart, for example, when we see stimulus like a bear, we start to run

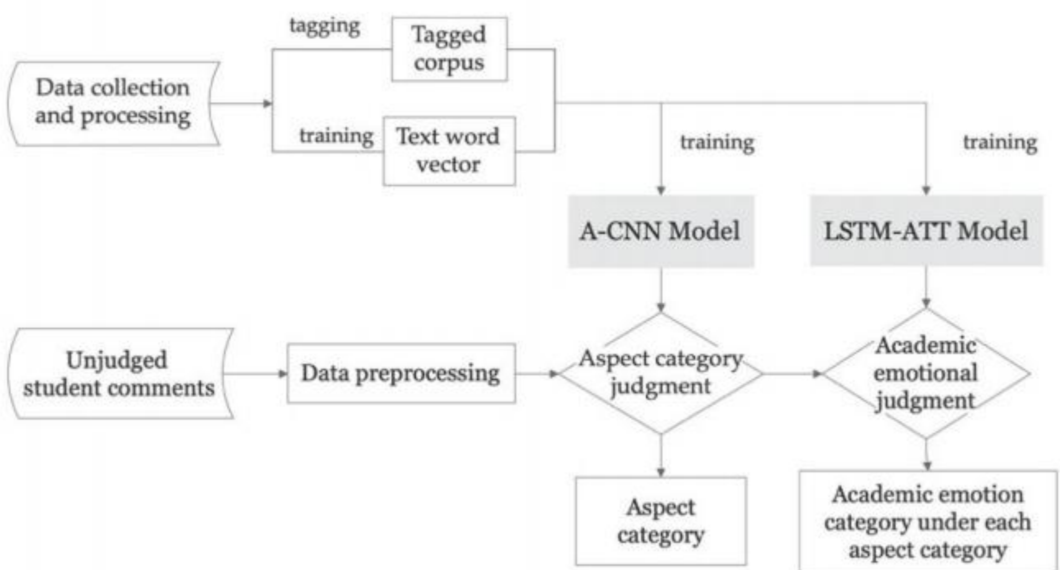

Figure 2. Academic emotion automatic recognition pipeline framework

and then are afraid. We're not running for fear; we're afraid of running. When his Danish friend Carl Lange offered a similar perspective independently in 1885, that theory has since become known as the James-Lange theory of emotions (Kowalski and Westen 2005 p348, Candland et al 1977 p87). The alternative theory suggested by Walter B. Cannon (1927-1931) that emotions are more cognitive than the physiological state of excitement.He saw the sequence of events as external stimulation and neural treatment and physiological reactions. Philip Bard broadened Cannon's theory by demonstrating the thalamic structures of emotion expression, which became known as the "Cannon-Bard Theory" general theoretical position This new theory included that stimuli that produce emotions simultaneously generate an emotional experience such as fear and corporeal responses like sweating (Candland et al. 1977 p87-88, Kowalski and Westen 2005 p348).

The study examined recognition at the perceptive level (experiment 1), and at semantitic level (experiments 2 and 3), in children who were autistic (N = 20) and normally in developing children (N =20) of standard face expressions of emotion (anger, fear, disgust, happiness, sadness, surprise). The results showed that kids with autism could recognise all six emotions at different levels and made the same type of error as children with autism (4).

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These negative findings are discussed in relation to 1) earlier data showing a particular autism impairment to recognise the believe based explanation of surprise, 2) earlier data showing a particular autism impairment to recognise fear and 3) convergence of findings that persons with autism pass a basic emotional recognition test but do not recover, such as patients with amygdale

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Since KANNER (1943) first described their lack of emotional contact with others in the original clinical account of children with autism, psychologists assess the deficiencies in autism in social and affective conditions. The empirical study on the emotional impairment of autism in children and adults is extensive and diverse so that the results are not surprising. The general emotional deficiency assumptions (Baron-Cohen etal. 1999; Howard etal. 2000; Hobson, 1986a; 1986b; Hobsonet al., 1988) and a selectivity emotional deficiency were explored.Furthermore, mind theory (ToM) deficiency accounting for autism allows research on selective emotional disorder through contrasting recognition tasks that do not require the ability to represent mental states (Baron-Cohen et al., 1993). The present research seeks to replicate and extend these findings with autism-based children.
Deep Learning (deep learning) was created by Rina Dechter in 1986, [2] by Igor Aizenberg and collaborators in 2000 for machine learning and deep learning for ANN, with a history of Boolean threshold neurons [3] via neural learning networks.In 2006, an announcement by Geoff Hinton, Teh and Osindero[4] showed that, as individual labels in exchange for non supervised feed, it would be finished by applying supervising back propagation[5], in which way a full-layer feed-forward NN would actively pretrained layer by layer at a time.

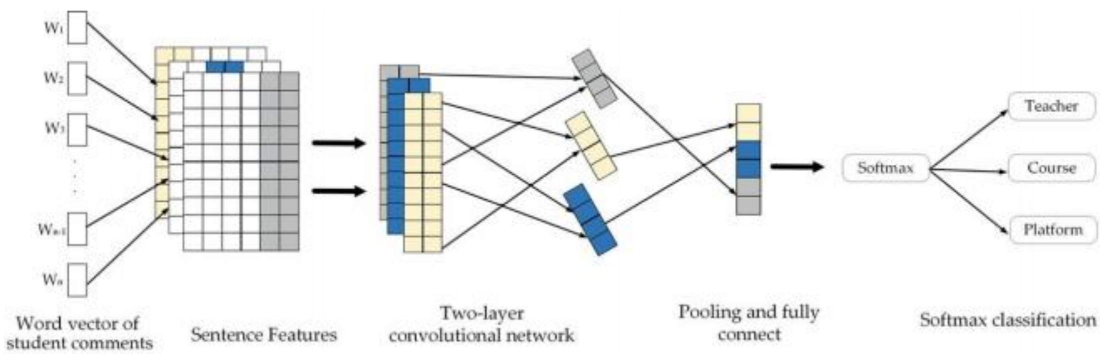

Figure 3. The aspect-oriented convolutional neural network (A-CNN) model

Many researchers have developed and analysed different methods for recognising human emotions from different facial expressions. Researchers used methodology such as a deep study algorithm (Deep Learning Algorithm), Viola-Jones, Haar Cascade Classifier, LBPH, and K-Nearest Neighbor to recognise face expressions.Researchers have shown different precise results by using these algorithms, and have defined an improved model that fits the relevant data set (s).
Many studies have used CNN to select and optimise active facial regions rather than the entire facial area. CNN has been used by researchers[10] to extract features from three optimised regions of the active face: left eye, right eye and middle mouth. Researchers[11] recently developed a model that can predict primary and secondary emotions by analysing CNN.Authors selected the appropriate features from extracted dynamic characteristics of the Neural Network Clasifier by using trust points and feature selection method and observed 99% accuracy. Researchers[12] also introduced a system for emotional recognition by CNN and Recurrent Neural Network on video data (RNN). Study[13] looked into emotions by using a deeper neural network, grouping them into six categories. In [14] authors showed interest in the idea that the visual concept is based on a structure of CNN. Viola-Jones algorithm[15] uses convolutionary neural networks for the detection of the face and for the deep learning of the face.92.81 per cent of this system has achieved high precision. In general, researchers use CNN to establish high accuracy in recognising facial expressions appears prominent. In addition to these studies, some researchers[16][17] used a method of profound learning and transfer to identify a minor leaf condition. You proposed a concept of helpful learning where

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the emotions from an image are categorised into eight categories in a deep learning model. Researchers have[18] been using dual-feature fusion to recognise seven emotions.They have detected facial expression with the use of Viola-Jones algorithm[19] in a restricted environment using both structure and geometric feature and gain average accuracy of 98 percent. The CMU-MultiPIE database has been used. The Viola-jones hair cascade researcher [20] used AvaBoost's Active Shape Model. They claimed 98 per cent more precision in still images is provided by the systems. 97.3% with limited emotional exercise samples under various illuminations worked to improve accuracy.The Hair Wavelet Transform (HWT) and Gabor wavelets have been used by global and local feature extract researchers [21], respectively. Some scientists used Local Binary Patterns (LBP) and calculated LBP with separate four-neighbors and diagonal neighbours. In the case of JAFFE, CC, FERG and FEI face databases in noisy and noise-free conditions, their study has shown an improvement in recovery rates. Researchers[22] applied k-NN classifier and MLP neural network for function classification to analyse seven emotions and calculate features for a three-dimensional face model.LSTM-ATT mainly has five layers: input, word vector training, LSTM network training, attention, and output layers (Figure 4)

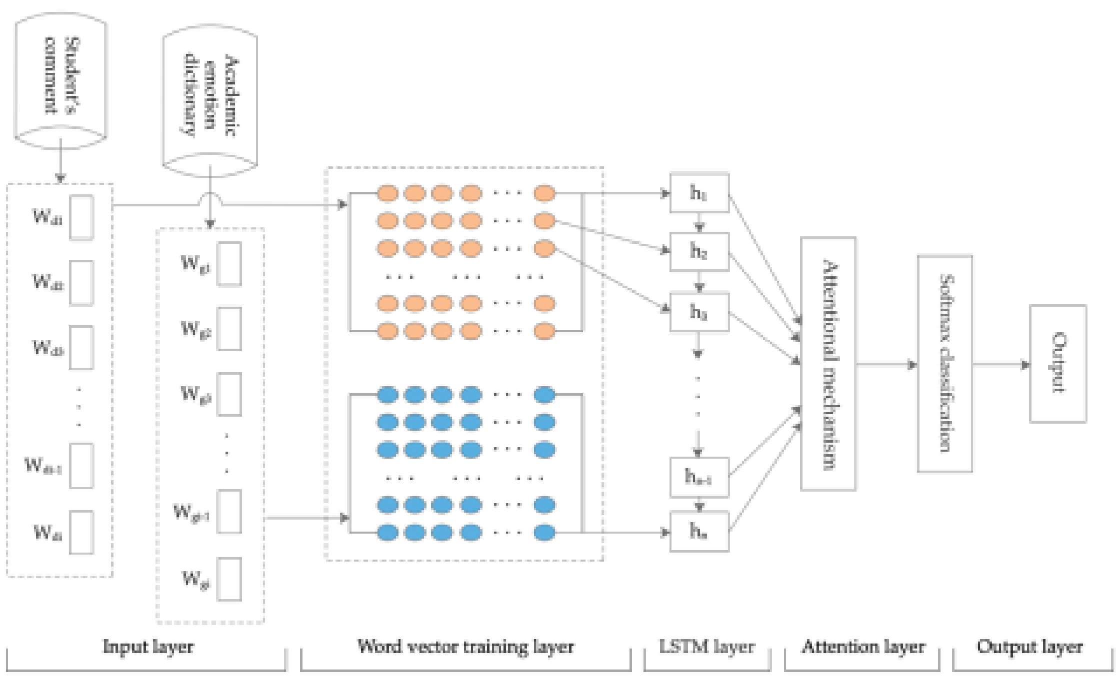

Figure 4. The long short-term memory with attention mechanism (LSTM-ATT) network model

II.CONCLUSION

Numerous researches and studies about Emotion Recognition, Deep learning techniques used for recognizing the emotions are conducted. It is required in future to have a model like this with much more reliable, which has limitless possibilities in all fields. This project tried to use inception net for solving emotion recognition problem. various databases have been explored, Kaggle’s and Karolinska Directed Emotional Faces (KDEF) is used as dataset for carrying out the research. Tensor Flow is used to train the model. Accuracy rate of about 39% is achieved. In future, real time emotion recognition can be developed using the same architecture

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