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Human Emotion Tracking System Using Deep Learning framework and Knowledge Graph

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Abstract: Human emotional tracking is a huge challenge. To address this work focus on the proposed research model HEDA that combines human emotions tracking using knowledge graph. The work uses PAFEW dataset to focus on the outcomes of the proposed work. The work also addresses the human physiology behavior using the concepts of EDA. Research in the area of emotion recognition based on electrodermal activity (EDA) tries to identify and categories human emotions by analyzing physiological data, especially changes in the electrical conductance of the skin. Emotion identification algorithms can be made more accurate and interpretable by incorporating a knowledge graph into the process.

***Keywords**: HEDA, EDA, Knowledge Graph, Human Behaviour.*

1. Introduction

Research in the area of emotion recognition based on electrodermal activity (EDA) tries to identify and categorize human emotions by analyzing physiological data [1], especially changes in the electrical conductance of the skin. Emotion identification algorithms can be made more accurate and interpretable by incorporating a knowledge graph into the process [2]. The concept to ER needs the following information to convert ER into knowledge graph. Before initialization the data are collected and fed into knowledge graph construct and its followed by entry and relationship extraction [3]. The subjected data are further categorized as Interoperability and evaluation refinement.There is a lack of empirical research within the academic field of IT security that tries to measure the amount of human influence [2]. Some existing empirical studies analyse user perception, behaviour and attitude towards computer ethics and information security [3-5], as computer security and computer ethics are important components of the management information system [6].

2. Background

EDA measurements and the related emotional labels are required to create an emotion identification system based on these measurements [4]. Galvanic skin response (GSR) sensors, which track variations in skin conductance, are one type of sensor that can gather this information.A knowledge graph is a semantic network that shows the connections among various items. A knowledge graph can be used to represent several components of emotion recognition [5][6], including the emotions themselves, their causes, the physiological reactions they are connected with, and the context. Establishing entities (nodes) and relationships (edges) between them is necessary for building a knowledge graph [7].

The relationships between the extracted entities should be identified and defined. For instance, you can find links between emotions and their possible causes [9], the physiological changes that go along with particular emotions, or the moderating elements that affect the correlations between emotions and EDAs [10].Sync the knowledge graph you created with the EDA information you previously gathered [11]. This integration may involve making connections based on the linkages shown in the knowledge graph and mapping the physiological measures to the associated nodes. Using the combined EDA data and the knowledge graph [12], build a model that can predict emotions using machine learning or pattern recognition techniques. The model may infer associations from the graph's encoded relationships and make predictions based on EDA patterns that have been seen [13].

The interpretability that a knowledge graph offers is one of its key benefits. The reasons for the predictions made by the emotion recognition system can be explained using the relationships stored in the graph [14]. Users may be able to comprehend and trust the system's output as a result.

Utilize the right metrics to assess the effectiveness of the emotion recognition system, and if necessary, make adjustments to the model and knowledge graph building.

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Adding more domain knowledge, growing the knowledge graph, or investigating other emotion identification algorithms are all examples of refinement.

Emotion identification algorithms can gain from a fuller representation of emotional occurrences, environmental circumstances, and physiological responses by merging electrodermal activity measurements with a knowledge graph [15]. The ability to recognise emotions may become more precise and explicable as a result of this integration.

3. Methodology

Data Collection:

EDA Sensors: Get the right EDA sensors or equipment for monitoring changes in skin conductance [16][17]. Galvanic skin response (GSR) sensors or other tools made to record EDA signals can be among them.

Emotional Labels: Gather a dataset of emotional states that are labelled to match the EDA measurements. Participants can self-report these labels[18], or they can be discovered using other techniques like video analysis or physiological response annotations.

Knowledge Graph Construction:

Entity Extraction: Determine and extract entities that are important for emotion recognition, including emotions, physiological ideas, environmental considerations, and any other pertinent data. A survey of the literature, professional annotations, or resources relevant to a given topic can do this.

Relationship Extraction: Based on current information or professional insights, determine and specify the relationships between the retrieved items. Create connections that stand in for affiliations, dependencies, dependencies, and any other pertinent interconnections.

Data Preprocessing:

EDA Signal Processing: The raw EDA signals from the sensors that have been preprocessed [19]. Techniques including filtering (such as low-pass and high-pass filters), baseline correction, noise removal, and feature extraction may be used for this. Skin conductance response, skin conductance level, and various statistical metrics are often utilised characteristics.

Knowledge Graph Preprocessing: Make sure that the entities and relationships are accurately recorded and prepared for integration with the EDA data by organising and preprocessing the knowledge graph data [20].

Mapping EDA Data to Entities: Connect the knowledge graph entities that correspond to the preprocessed EDA features [21]. This mapping may be based on feature similarity, temporal alignment, or other pertinent factors.

Linking EDA Data to Relationships: Make links between the relationships in the knowledge graph and the EDA data. In this step [22], the physiological measures are combined with the conceptual and contextual data stored in the graph.

Model Training and Evaluation:

Machine Learning Model: Create a pattern recognition or machine learning model that is appropriate for recognising emotions. The integrated EDA data and the knowledge graph can be used to train this model [23].

Cross-Validation: To evaluate the effectiveness of the emotion recognition model, use suitable evaluation methods like k-fold cross-validation. Consider criteria like accuracy, precision, recall, and F1 score when assessing the system's performance.

Interpretability and Explanation:

Use the knowledge graph to give the emotion recognition system interpretability and explainability. Extract pertinent data from the graph to support the system's predictions and reveal connections between feelings, bodily reactions, and environmental circumstances [24].

Refinement and iteration:

EDA-Based Emotion Recognition

The goal of electrodermal activity (EDA)-based emotion detection is to identify and interpret human emotions by examining changes in the electrical conductance of the skin. EDA is intimately correlated with the autonomic nervous system's activity and can shed light on emotional arousal and thought processes [25]. The following setup are deployed to accomplish EDA emotional recognition.

EDA Sensors: Invest in EDA measurement tools like GSR sensors. By monitoring changes in sweat gland activity, these sensors can identify changes in skin conductance [26].

Participant Preparation: Participants should be comfortable and free of any lotions or oils that can interfere with the EDA measurements. They should also make sure their skin is clean.

Experimental Design: Create research or experiments to evoke particular emotional states or collect information in realistic environments [27]. This may entail giving participants emotional cues, involving them in emotionally charged activities, or documenting EDA in actual life scenarios.

Once the data is collected and the preprocessing is initiated based on

Sensor Placement: To take accurate readings, place the EDA sensors correctly on the participant's skin [28], typically on the hands or palm.

Data Sampling: To record EDA signals with a good enough temporal resolution, set the sampling rate for data acquisition, which is normally in the range of 10-100 Hz.

Data Preprocessing: Apply preprocessing methods to the collected EDA data, such as baseline correction, noise and artefact filtering, and artefact removal (if required).

Finally the Feature extraction and classification phase does the identification the traits connected to emotional responses, extract pertinent features from the preprocessed EDA data and the common features included like Skin Conductance Level (SCL) and Skin Conductance Response (SCR

Slope and Amplitude: The SCR waveform's amplitude and slope [29].

Peak Features: The SCR peaks' area under the curve, peak amplitude, and time to peak.

Feature Selection: Use feature selection techniques if necessary to find the most illuminating features for emotion recognition.

Emotion Classification

Machine Learning Algorithms: Train a machine learning model to categorise emotions based on the retrieved EDA features, such as support vector machines (SVM) [30], random forests, or neural networks.

Training and Testing: Create training and testing subsets from the dataset. The model is trained using the training data, and its performance is assessed using the testing data.

Performance Evaluation: To evaluate the effectiveness of the emotion classification model, take into account its accuracy, precision, recall, F1 score, and other suitable metrics.

Cross-Validation and Generalization

To assess how well the emotion recognition model generalises over various subsets of the dataset, use cross-validation techniques like k-fold cross-validation. Addressing Overfitting: Utilise parameter tuning and regularisation methods to reduce overfitting and enhance the model's capacity to generalise to new data.

Interpretation and Analysis:

Analyse the patterns in the emotion categorization to interpret the results. Analyse the connection between the emotions that were recognized and the relevant EDA patterns.

Correlation with Other Modalities: For a more complete knowledge of emotions, think about combining EDA data with other physiological signals (such heart rate, facial expressions, or self-reports) or subjective measurements.

4. Proposed Work

Knowledge Graph

A structured information representation known as a knowledge graph includes entities, their qualities, and the connections among them. It offers a mechanism to arrange and link data in a graph style, where nodes stand for entities and edges for connections between those things. Knowledge graphs make it possible to combine many data sources and make knowledge search, inference, and reasoning easier.

The PAFEW Dataset

The PAFEW (Pain, Affect, and Facial Expression in the Wild) dataset is an assortment of physiological signals and facial emotions that were recorded in actual life situations. It is made to aid in affective computing research and development, emotion identification, and pain detection.

Key features of the PAFEW dataset include:

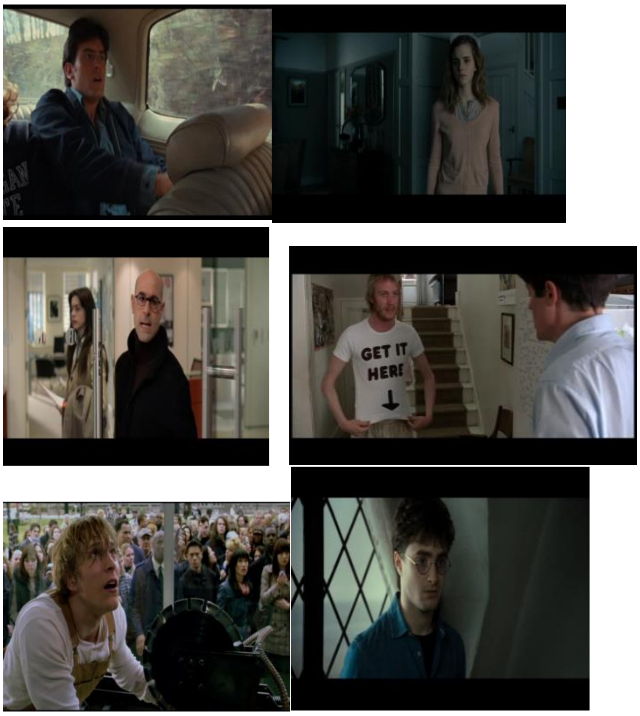


Fig:1 Images from PAFEW Dataset

- Real-World Context: In comparison to controlled laboratory conditions, the dataset collects physiological signals and facial expressions in natural situations, offering a more ecologically realistic portrayal of emotional and pain-related reactions.
- Multimodal Data: PAFEW combines facial expressions with physiological information from the electroencephalogram (EEG), electromyogram (EMG), electrocardiogram (ECG), and electrodermal activity (EDA), among other data modalities. The investigation of the connections between facial expressions and physiological responses is made possible by the multimodal character of the data.

- Large Scale: With the help of numerous video clips gathered from various sources, PAFEW has created a sizable dataset for training and evaluation. The dataset's diversity in terms of people, expressions, and scenarios improves its representativeness.
- Annotations and Labels: Annotations and labels are provided by PAFEW for a number of different characteristics, such as face action units (AUs), fundamental emotions, pain severity, and physiological signals. The ground truth data provided by these annotations is used to train and assess models.
- Challenges and Variations: The dataset includes a variety of difficulties and modifications, including changes in lighting, head postures, occlusions, and various pain or affective intensities. The dataset is more difficult and realistic for algorithm development and evaluation because of this fluctuation.

The PAFEW dataset's accessibility has helped enhance research in affective computing, pain detection, and emotion recognition. This dataset can be used by researchers to create and test algorithms, train machine learning models, investigate multimodal fusion methods, and look into the connection between physiological signals and facial expressions in realistic settings.

Although the PAFEW dataset is a well-liked resource, its precise specifications and features could change over time. The most current and correct information should always be found in the original papers and sources linked to the dataset.

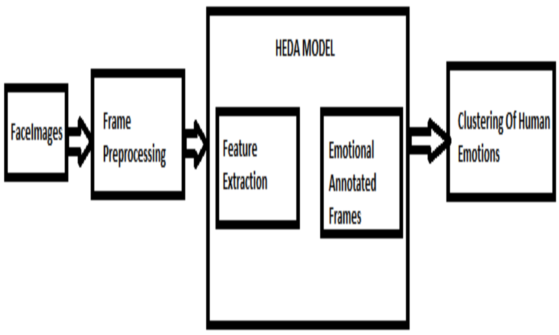
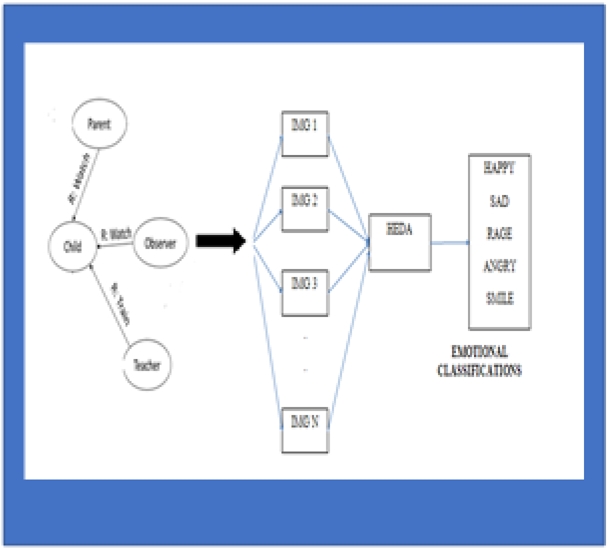
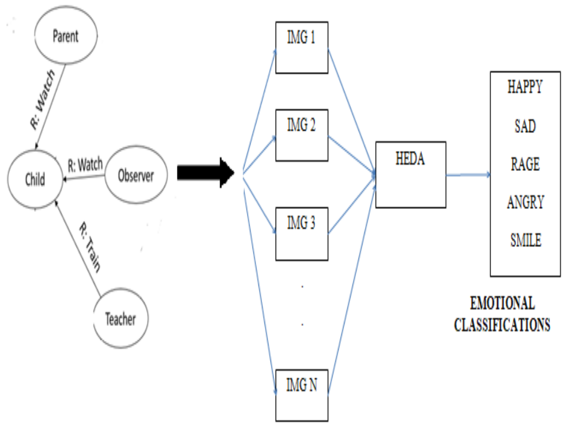
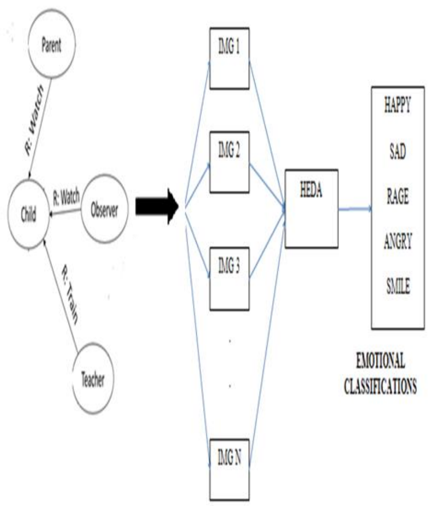


Fig:2 Methodology of Human Emotion Detection Analysis Model







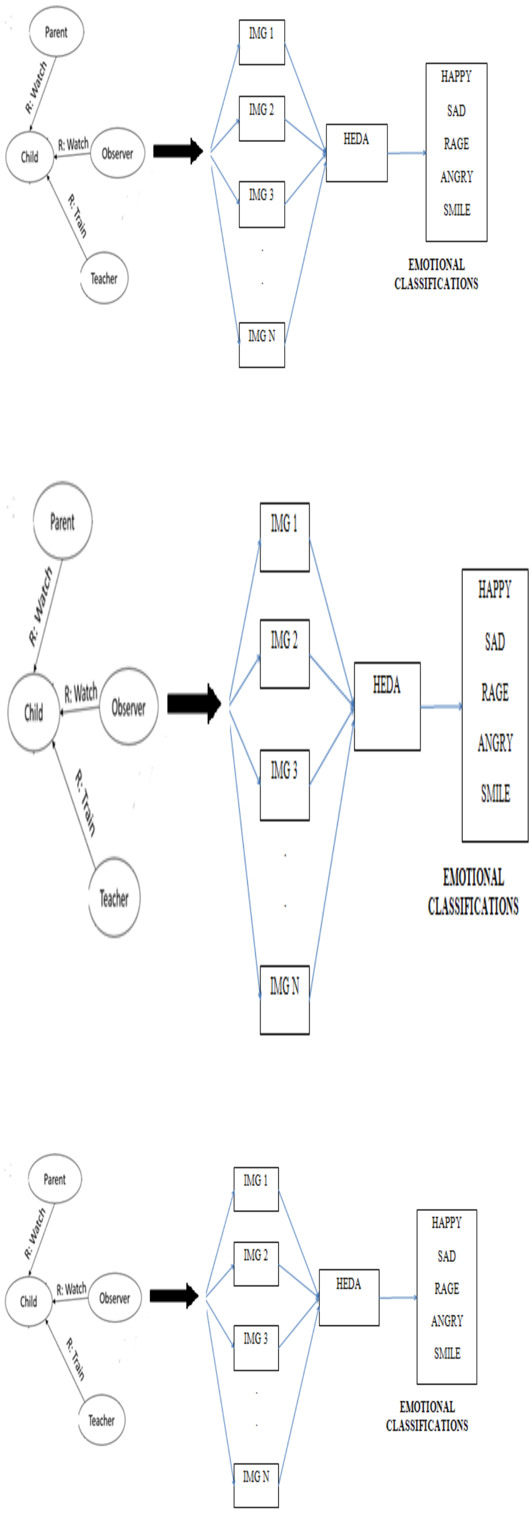


Fig 3:Knowledge Graph input to HEDA Model.

HEDA Algorithm

Based on the observation, let the set of objects defined as {, …..} where o is the objects.

Every objects is associated with the person emotions declared as

o∈ P_(i,) Where P is the persons and i is the emotions.

Hence where objects are associated with the person linked based on emotions.

Every association with the objects is represented as

$$o \in p \in f \quad (1)$$

f in eqn(1) represents emotional quotient that makes the association between emotions

$$f: o_n \to p_i \quad (2)$$

Every object is associated with the person and their emotions.

Identification of emotions is represented using composite operator ∂ where

$$\partial(o_n \to p_i) = \partial(e_n) \quad (3)$$

Where e is the emotion identification.

The emotional identification is defined as

$$\forall(f) = V_{O_n}^{P_i} e_{(i*n)} \quad (4)$$

RESULTS AND DISCUSSIONS

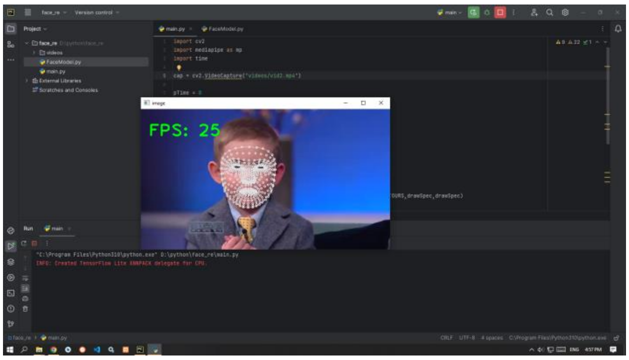


Fig 4*:* Detects face and checks for emotions

Fig 5*:* Image that detects and interprets human facial emotion.

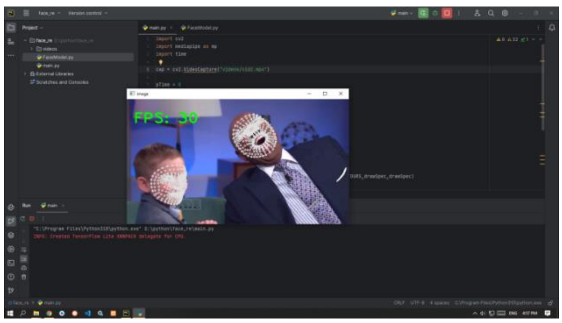


Fig 6: Detects two different laugh face emotions and displays them as a graph

Fig 7: Detects multiple people and their emotions

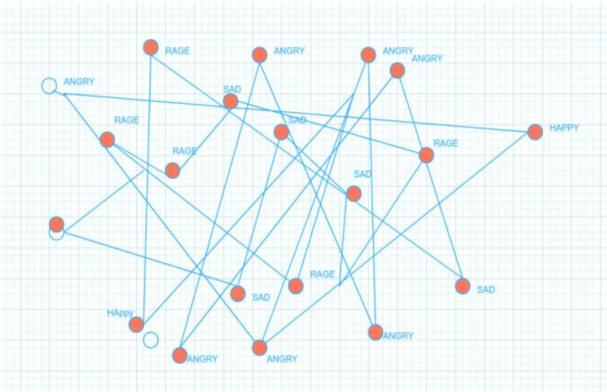


Fig 8: *Emotional link represented using knowledge graph*

5. Conclusion

This work proposed HEDA model to identify people emotions using PAFEW datasets. Objective is to identify different emotions of different people in a single frame. The results achieved shows that the emotional identification is mapped with the same emotion made by different person in the same frame. The results identifies same emotional shown by the people and shows the group emotions. In future the work will gives the emotions in terms of count where overall emotions can be tracked by the system to know the people mind set rather than fake inputs.

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