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Machine Learning based Emotion Recognition using Facial Action Units over Edge-based Academic Infrastructure

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Abstract

Edge-based applications are envisaged to have a paramount impact on the academic landscape. One of the key aspects of academic activities is to keep the learners engaged. The pertinent engagement activities require constant analysis of the learner's emotions and expressions. Both aspects of comprehending the learner's engagement greatly rely on facial coding/recognition systems. Facial recognition widely depends upon the component analysis of facial action units which are structured sets of semantic features. This research proposes a lightweight machine learning-based framework for edge-driven gadgets with five major modules and 68 recognized points of interest in each image of 360x360 dimensions. It exploits Support Vector Machine (SVM) and Convolutional Neural Networks (CNN) to recognize the audience, capture expressions and semantically label emotions. Hence, a real-time adaptive feedback-based experience can be enhanced through dynamic interaction for improvising the outcomes of learning activities. The Extended Cohn-Kanade (CK+) dataset has been employed through an extraction function that classifies several learner emotions. The expressions and emotions of the audience during interaction were taken as input to the proposed model and maintained in the dataset along with the output. This feedback identified the spectators' requirement for better interaction and more focus on engaging the learners. An overall accuracy of 98% was achieved in correctly predicting the learner's emotions by the proposed approach, as highlighted through standard machine learning metrics. The potential future directions are deep-learning-based gesture analysis, improving the precision for spectator feedback and efficiently catering for the computational requirements.

Keywords: Deep Learning, Edge for Education, Emotion Analysis, Facial Recognition, Gesture Analysis, Machine Learning

INTRODUCTION

Emotion Analysis plays a vital role in taking the opinions of academic learners through the semantics of positive or negative gestures, efficiently. Expression or Facial actions are the tools which reflect the learner's experience. Facial emotions and expressions have taken diverse attention in recent decades because of immense applications in different fields. Facial analysis of the audience allows the observer's welfare and reflection during real-time interactive activities. It has been highlighted that there are eight primary emotions like joy, sadness, acceptance, disgust, fear, anger, surprise and anticipation (Plutchik, 1988). Furthermore, according to research, it is possible to detect multiple faces in video or through real-time camera gadgets (Edwards, 2001). In real-time videos, images can be taken at a particular time frame and processed for machines. This processing is carried out at conjecture of expression and resizing of image to a required size. The system further processes the incoming video streams, while consuming minimum resources in terms of bandwidth and latency esp. over edge-based infrastructure (Majumder, 2016). Facial expressions are accountable for transmitting the data that is hard to interpret. It provides a person's mental state that is directly related to his or her intentions to attain the learning goals required. Emotional marketing is currently a new dimension for customer's feedback as it establishes that consumers buy for emotional reasons rather than a need.

Robots and avatars are previously programmed in order to adapt to user commands. Recent advancements in software systems, computer vision and machine learning are the basis of artificial support services that can accurately detect and react to the emotions. Apple's Siri (Wankhade, 2022) is perhaps the first era of emotionally smart and intelligent machines. From all over the globe, computer experts, psychologists and evolutionary biologists are constantly working to achieve the best sensor techniques and algorithms for HCI (Human Computer Interaction) based emotion analysis requiring minimal latencies and bandwidths in prevailing ubiquitous ecosystems.

Facial expression recognition is a research problem related to image processing. It is a complicated and difficult task for machines but for humans, it's easy to analyze and categorize the basic emotions along with the semantics of facial expressions. All emotions are directly connected to a single facial nerve with a corresponding facial action unit. Each facial action unit is the result of subjective feeling. The difficult task in emotion detection is configuring differences in emotional intensity. For example, happiness and excitement may present different levels of intensity for the basic emotion of happiness and may be classified at a finer level of granularity.

Current research targets to provide a unique approach for discriminating the facial actions and emotions by using "wheel of emotions" for seven basic emotions/expressions, as discussed in section 2. It may be used to define the audiences' valence and active state from usability to user experience on academic landscape. We concentrate on aspects if an individual feel engaged while using item or service/content that is offered or created. This analysis has also validated the information by domain experts as captured through gadgets (in labeling emotional states) of real-time and accurately over edge infrastructure. The aspects that were considered in measuring emotions are colors, layers and relation. The proposed technique operates quickly and is stable across actual moments through all stages of the recognition method.

In the proposed framework (illustrated in Figure 1), video recordings (as frames) of all sessions evaluated the recorded behavior of participants to validate the face-emotion image recognition with following milestones:

- The pre-processing activities have been performed to obtain precise and quicker outcomes on the algorithm such as feature extraction, conversion of picture to gray scale and normalization of picture dimensions.

- It operated in real time, saved the photos on the disk, detected the face on the image, extracted the facial features, and ultimately classified the emotions based on the Viola Jones approach (namely Haar Cascade Principle) using KLT Algorithm.

- Support-vector machine (SVM) has been used as classifier and for regression analysis of facial emotions.

SVM outputs an optimal hyper plane identifying new examples to be trained. This enabled us to achieve a relatively higher degree of precision (roughly 78%), but the system was slow and the photos took much disk space (even if automatic photo deletion was performed after the proper classification). By using Wheel of Emotions, sub emotions were identified along with placement of arousal and valence, describing the engagement of learners.

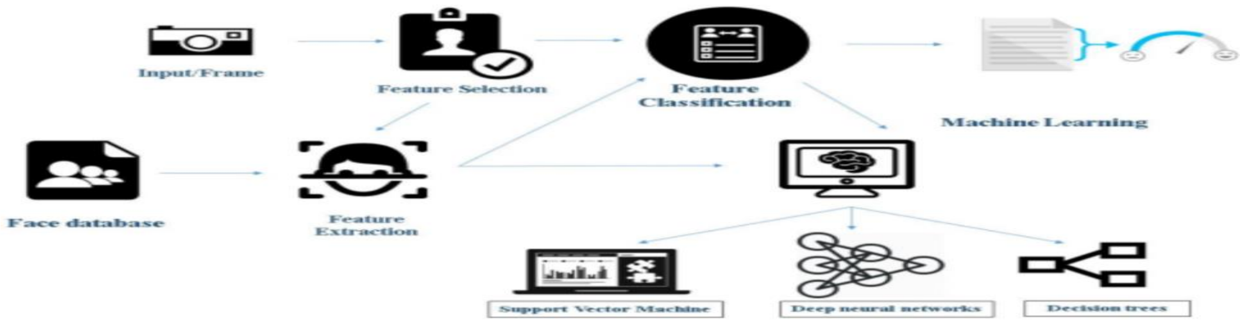

Figure 1.
Architectural View of Proposed Framework

The tests were contrary to the computer findings and revealed a total value of 83.95%. It represents an average accuracy of software based on the emotions requested and as acknowledged by domain experts through psychophysical analysis. The rest of the paper is organized as follows; Section II covers the research background and literature review; Section III presents the proposed methodology with associated details. Section IV presents the experimental results, and Section V provides the conclusion while highlighting potential future directions.

LITERATURE REVIEW

Back in the past a book provided five universal emotions which everyone has in common, regardless of where or how we are raised (Wankhade, 2022). Most researchers of emotions agree on these five universal emotions. Some researchers might think that fundamental feelings are not taught, but innate. For instance, individuals who are born blind and never saw faces still reveal the quintessential facial expressions of basic sentiments (Acheampong, 2021). In another research the researcher built a hypothesis to find out whether expressions are universally understandable among humans or they are facing difficulty in it (Elizabeth, 2020). The research started to analyze the basic emotion whether they have facial expressions or not. Previously there had research in which the use of machine learning based on the information from Photographic Affect Meter to forecast mental states with detrimental interest. and offered a routine aggregation strategy to track substantial negative events (Musolesi, 2019). There is empirical proof that machine optimization algorithms could be used efficiently for this prediction mission. The interaction between human and robot spoken was mainly a small conversation with patients who had no real task to do. Keyword identification is operated for specific tasks such as "Locating a remote control" (Nasralla, 2022). This research mainly focused on the development of a psychological processing system that includes dialog and digital character reaction strategy.

There are few fundamental feelings (Table 2.1) that are valid for every age and cultural distinctions (Plutchik, 1988) (Elizabeth, 2020), and are credited for the universal recognition of six feelings (anger, happiness, fear, surprise, disgust and sadness) (Singh, 2022). There was another model developed to introduce a new scheme for the classification of three-dimensional emotions (Ahmad, 2019). These axes describe the valence, arousal and intensity of emotions. Many studies relate to a two-dimensional model based on the circumplex model (Singh, 2022).

A structure for the real time emotions detection in e-learning through webcams was introduced (Structure for Enhanced learning via webcams and microphones) (Westera, 2014). Based on learner's facial expressions and verbalizations it provides prompt and appropriate input. The Learning Management system (LMS) (Wang, 2012) and other domains other than LMS process assessment revealed that the expectations of software are classified with parameter analysis, interactivity, utility, helpfulness and preparation for potential use.

Another research explained through progressing cognitive computation and psychology, the quiver of psychological measurement tools was expanded (Caballé, 2011). Today's methods range from simple measures of pen and paper to genius software which test brain waves and eye traction. Nevertheless, there are still not enough empirically demonstrated approaches to resolve the adequacy of every approach in relation to the requirements and gravitational anomalies of the calculation. The research had showcased the implementation and design of emotional classification system throughout real time (Prikler, 2017). It is described that the range of positive to negative emotions, and arousal the active to passive scale. High valence and arousal reveal an agreeable and active sensation, describing feelings like happiness and motivation (Ahmad, 2019). The two-dimensional emotional scheme (Singh, 2022) (Schlegel, 2012) can be allocated as presented emotions in Figure 2.

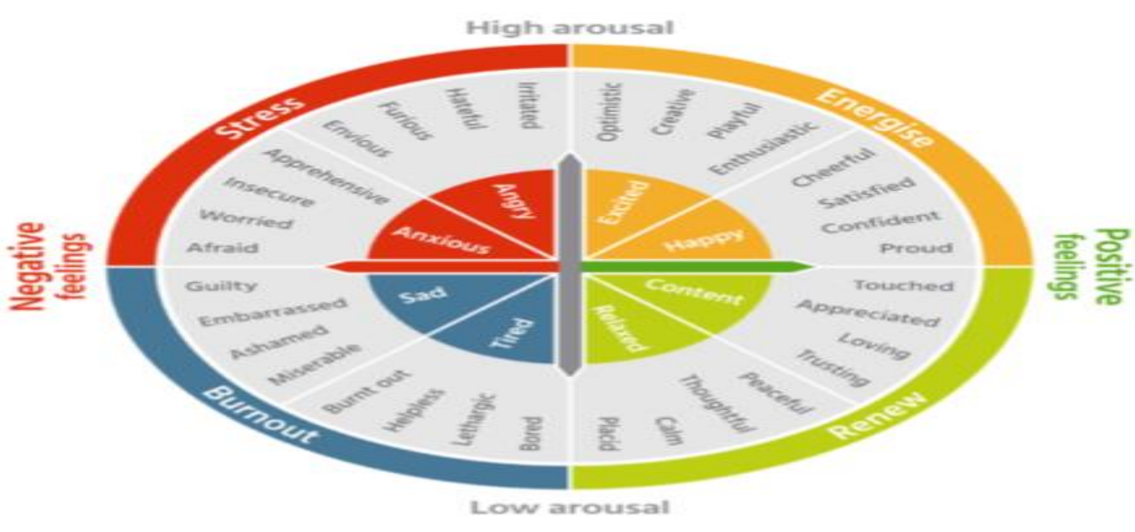

Figure 2.
Russell's two-dimensional Emotion Model

According to two different researches, it is difficult to select the feature selection techniques in various conditions of different skin color, gender or lightening effects (Harrigan, 2013) (Moore S., 2011). Appearance features are difficult to generalize while

Geometric features are more dependent on exact features of facial expressions. Features extraction and classification techniques are difficult to choose. Geometric and Appearance features are two main categories under feature selection. The features can directly be extracted through Action Units points or straightly be covered under basic emotions by automatic facial expression recognition systems (Wankhade, 2022). According to another research diverse outputs of expressions are generally illuminated but more accurately recognized than displays of moving places (Wegrzyn, 2017). The comparative utility of both upper and lower facial regions was also studied utilizing standard lit and spot-on displays to classify these six emotions. In both situations the results show that multiple facial regions are more descriptive of deep emotions.

There is also discussion of motion patterns that characterize diverse emotional expressions and common confusions between emotions. Furthermore, it was added in a research that the modern pathway is made up of 4 phases in the contemporary area of recognition i.e. discovery, alignment, classification and representation (Ranzato, 2014). This researched the orientation phases and the representation stage by using direct 3D face mapping to incorporate a piece by piece and create a facial model from a deep neural network of nine layers. Instead of the traditional overhead layers, this deep network contains over 120 million parameters using several locomotive connected layers without weight sharing. It made the models heavier to proceed in real time detection and classification over edge devices.

The design of the network is supposed to take therefore that the direction of every facial area is adjusted to the pixel rate once the alignment is done. It is thus feasible, without several layers of formalism, to learn from the RGB raw pixel attributes, as is found in many other networks. The self-organizing map (SOM) (Nasralla, 2022) based classifier is an unmonitored network that is adaptively developing its neighboring neurons into detectors of various vector patterns. This network is also referred to as the Kohonen network (Rejeb, 2022) (T., 2013). For Automatic Facial expression recognition system there are multiple algorithm developed so far. Independent Component Analysis (ICA) has been utilized to obtain facial characteristics and recognition and then attempts to forecast face expressions with the Support Vector Machines (SVM) classification (Bartlett, 2002) (Hassouneh, 2020) (Nikolaidis, 2007) (Zhou, 2010) also used the same technique for classification and (Pantic M. &., 2000) (Pantic M. &., 2004) (Mufti, 2006) showed how to use rule-based techniques to detect face expression and action units expressed in CK+ (Kanade, 2010) and MMI dataset (Pantic M. V., 2005).

A study (Moujahid, 2013) interprets facial expressions in continuous videos; they focused output of classifiers using head to establish separate temporal parameters of face behavior; which comes with a 3D-face monitor, including the 3D head position and facial movements concurrently. The use of the monitor is independent of classification and texture. They practiced two different plans: The first scheme utilizes a complex time warp strategy to interpret emotions where learning information is presented with temporal signatures in conjunction to different standard facial expressions.

In this current research, a framework is proposed to address the mentioned shortcomings. In the literature review, distinct ways are highlighted for face recognition and classification of emotions for the assessment of feelings. Learning processes differs with the effectiveness and precision of various facial recognition, classification techniques and computational overheads.

RESEARCH FRAMEWORK

The proposed framework is intelligent, effective in nature and maintains precision of various facial recognition/classification techniques. The modules, as illustrated in Figure 3, present the distinct stages to detect the face, extract features and classifying the images. The identification of facial expression involves both facial movement measurement and image processing.

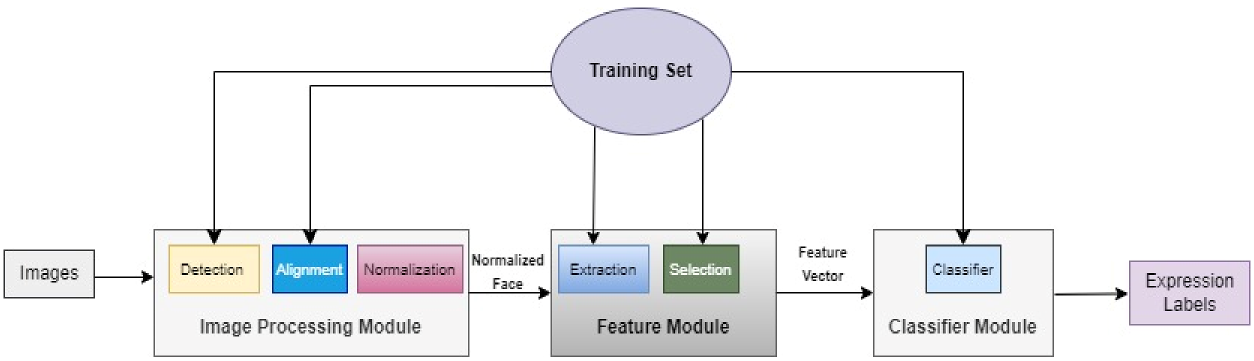

Figure 3.
Modules of Proposed Framework

A three-stage categorization has been performed for overall strategy of Automatic Facial Expression Analysis (AFEA): Face detection, Extraction and classification of facial characteristics and Facial expressions recognition. These three components have been implemented through five major modules, namely (1) Detecting and Assessing feelings, (2) Face detection model and identification, (3) Sub Emotions Taxonomy, (4) Active and Inactive State Analysis, (5) Training-sets. The proposed structure consists of distinct stages to detect the face, extract features and classify images.

Detecting and Assessing Feelings

The primary objective is to develop and execute a mechanism for detecting and assessing human feelings on facial expression analysis using an edge-based webcam gadget, so that the resulting applications can evaluate the information accumulated. The proposed multi-dimensional array-based approach saves the image space and discards images after employing Voila Jones Face detection method (Hassouneh, 2020) with up to 98% accuracy of human face detection. Firstly, it converts the image to gray scale. The rules of face-to-face assessment of mental states are based on the rules of face-recognition. The entire method of assessment was split into three successive stages (Wankhade, 2022). Those stages are the identification and location in the complicated environment of the face in the picture, including normalization, the removal by classifying agent of suitable characteristics depicting the specified face expression and the associated expression. Depending on the approach used and performance of classifier selected, available libraries have been used for detection, extraction and classification methods in system design and deployment. Figure 4 illustrates the implementation view of proposed framework. Current research specializes in the following points on the principle of extended model of facial expression such as: detection of significant facial characteristics, Facial characteristics extraction, facial action units and landmarks classification, modeling Active/In-Active emotional prototype.

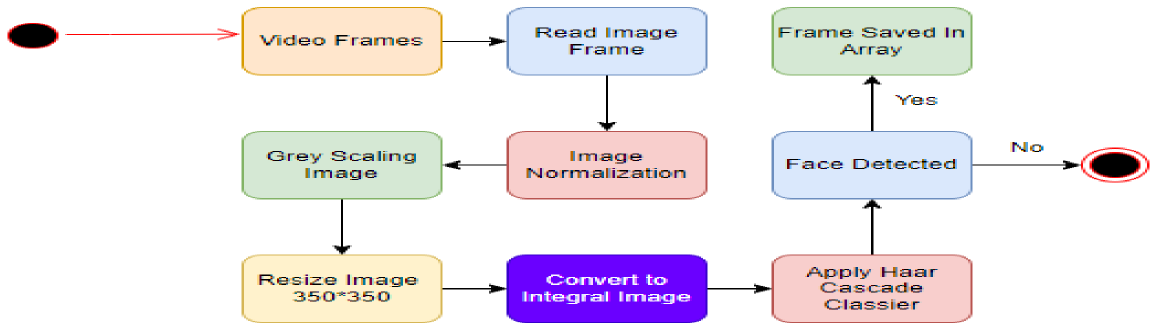

Figure 4.
Implementation Flow of Proposed Framework

Figure 5.
Emotion image classified as angry/happy

Figure 5 shows an angry/happy emotion that is classified by our model. The proposed framework uses pairing methods for templates that evaluate the correlation of the model to the picture's testing areas. The depiction of form, place, and orientation finds areas of interest are comparable to template. The sum of absolute differences, sum of squared differences, and standardized cross correlation are distinguished among formalized quantitative similarity measures used in image template matching. The two metrics offer a quick and easy assessment of the correspondence but it is important to take into consideration certain factors as well as robustness against noise, tolerance to deformation, lightweight computationally, the efficiency of a corresponding method with distortions, sizes and guidance differences.

Face Detection Model and Identification

Signified facial identification and extraction is done by the Viola-Jones algorithm (Hassouneh, 2020). The landmarks are then detected by 68 recognized points of interest for each rectangle which binds the image. All the 68 landmarks are mapped on the face for its detailed analysis and handle all necessary transformations of a frame to predict the facial expressions. Facial landmarks shape predictor library has been used to map the landmarks of detected human face. Then the detected faces from the original frame are extracted and a new frame, resized from the original frame is created based on the detected face of 360 x 360 dimensions. The detection of the face from the resized frames then further processed for landmarks and facial action units mapping. Extracted facial lines, head turn and a middle point between the eyes are shown for each face. The second component of knowledge methods is defined by a decrease in dimension which manipulates the whole area of concern with distinctive characteristics and key elements. Improving the precision of pattern recognition under monitored circumstances without important increases in handling moment; however, a well-organized atmosphere is necessary.

Sub Emotions Taxonomy

The main objective of this research is to examine how various participatory environments enhance the capacity of classification to categorize themselves for new faces. From the analysis and studies of James A. Russell the fuzziness of boundaries between basic emotions and sub emotions can further be described and assembled into sub categories of emotions making basic emotions tuple. Our research has taken these steps to categorize an algorithm for its post processing of basic emotions analysis. The main category of basic emotions is happy, angry, fear, sad, disgusted, contempt and neutral. The similar sub division of these basic emotions is as follow in Table 1.

The Algorithm has fully worked on the sub categories of basic emotions and the findings are as follows:

- The two maximums of happy and surprise will give resultant of delight.
- The two maximum findings of fear and surprise will give you alert feeling.
- Sleepy is the combination of two basic emotions sadness and happiness.
- Contempt is the mixture of two emotions angry and disgust.
- Drowsy is mix and match of sleepy and sad.
- Unpleasant is made up of sad and disgust. Relaxed feeling is combo of sleep and happy while trust is the combination of relaxed and happy emotions.

They can be further marked into subcategories but these emotions are enough for to describe the state of being active or inactive presence in the attendees.

Table 1.
Sub Emotions Classification

Basic Emotion	Sub-Emotions
Happy	Delighted, pleased, glad
Angry	Annoyed, Distressed, frustrated
Disgusted	Tensed, alarmed
Fear	Afraid, miserable, depressed
Surprise	Excited, astonished, aroused
Neutral	Calm, relaxed, serene
Contempt	Scorn, disrespect, ridicule
Sad	Droopy, bored, gloomy

Active and Inactive State Analysis

Through categorizing the emotions into sub categorizes we are now able to draw taxonomy of being active or inactive cognitive structure. Categorizing the verbal emotional expression is easy to plot while making its visual data is difficult to approach. This research has made a step up to find the audience emotions for the real time feedback and analysis of content.

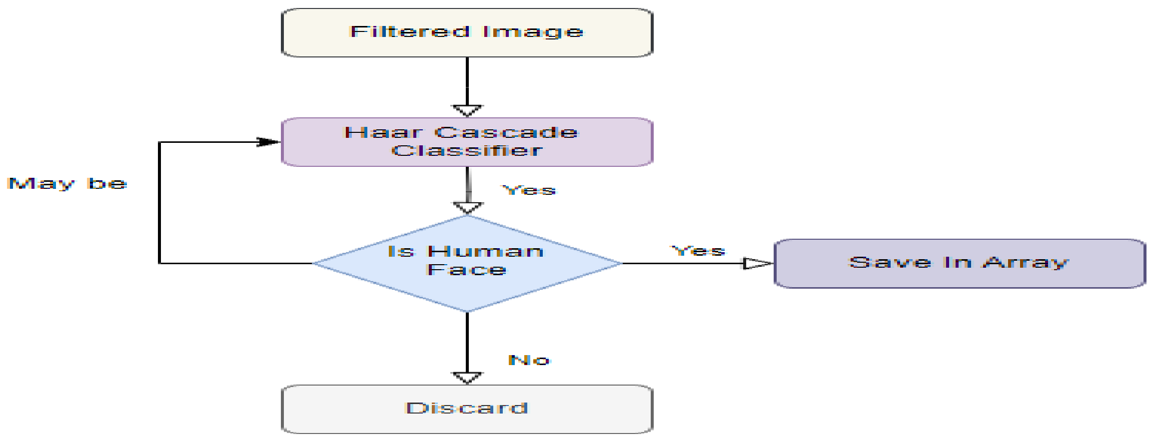

Figure 6.
Object Classifier for Face Detection

The algorithm is developed to sub categorize these sub emotions. These findings are directly related to the circumplex model. This approach is provided as both an expression of the structures and the cognitive framework used by lay persons in conceptualizing effects by the psychologists as evaluated by means of the auto report. Figure 7 shows the stages of identifying sub emotions classifier. Supportive proof was acquired by scaling 28 emotion-denoting adjectives in four various respects: Ross' method for the circular order of factors, a complex scaling mechanism centered on presumed resemblance between words, a reductive scaling of hypothetical joy-distress and degrees of arousal and an assessment of the 343 self-reports by the individuals. It could be said that community has an inherent concept of an analogy to the intrinsic theory of character or science. In fact, the spatial depiction of the emotion by lay people is probably intrinsic in the sense that few if anyone could clearly state their full conceptual framework.

Training-Sets

The Extended Cohn-Kanade Data set (CK+) (Kande, 2010) is a complete data set for action units and it is specified expression of emotion. The database of Cohn Kanade (CK) was launched in 2000 to promote research on the automatic detection of different facial expressions. CK + data set is a common data set comprising 593 video sequences of 123 items, plus 327 specific annotations, of the Cohn Kanade (CK+) data set. Seven styles of tags are available: dislike, joy, rage, frustration, anxiety, sadness and shock. The neutral to identified emotions are the source of every series. Figure 8 shows the Sequence of emotions in CK+ data set.

Figure 7.
Sequence of emotions in CK+ data set

Figure 8,
MMI data set images

Figure 8 shows the MMI data set, The MMI Facial Expression database is an ongoing project to provide the community of facial expression analysis with huge quantities of visual data for facial expression analysis and recognition. Google Facial Expression Comparison Data set is also used with the combination with MMT data set and CK+ data set for the efficient testing and output of the proposed technique.

EXPERIMENTAL RESULTS

The aim of the Machine Learning is to learn patterns which generalize well for invisible data, rather than simply storing the data shown during the training process. SVM and CNN have been used for performance applications automation and quest. The suggested classification category system and outcome optimization show better classification results. Through finer tuning, the better candidate functionality for classifications was selected. The layout of CNN contains two coalescent layers, 2 overall layers for pooling and a 256 neuron layer invisible. The model evaluation scheme further varies from Lopes et al. (Jones. M., 2001) analysis, which divides the data set into a training set, trial set and validation set and runs the test set many times to choose the best layout for the validation set during the K-fold cross-validation process. In order to further improve the CK+ express-ability of the software we substitute the 5x5-recovery kernel with two 3x3-convolution kernels in the reference model and remove the 7x7-recovery kernel with one 3x3 kernel and one 5x5-convolution Kernel.

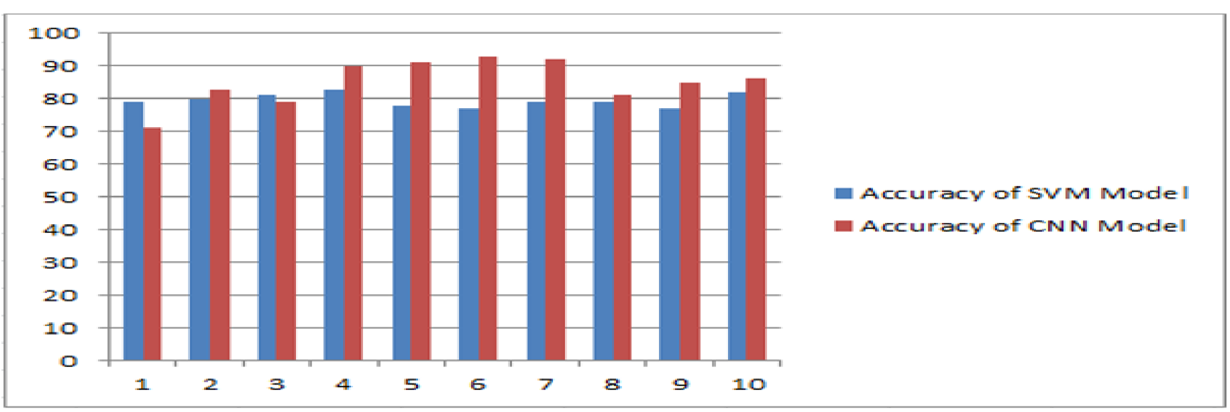

Figure 8.

Accuracy of Proposed Framework across 10 folds of cross Validation

In order to keep track of more options we continued adding two 3x3 layers and one pooling layer between the second and the fully connected layer and used 128 charts. This test gained an accuracy of 95.47 percent and reduces the error detection rate by 16 percent relative to the standard. We used three 3x3 turned core systems in the benchmark network instead of 7x7 turned core systems for further expansion of the network depth. Pre-training of our framework through CNN with certain auxiliary details improves the network's generalization performance. It requires much less time to retrieve target data collection from face features. The output layer acts as the SVM data, which helps in more accurate detection and its classification advantages. Figure 9 shows the accuracy across all 10 folds of data validation for CNN as well as SVM.

Table 2.
CONFUSION MATRIX (SVM MODEL)

Emotion	Anger	Contempt	Disgust	Fear	Happy	Neutral	Sadness	Surprise
Anger	0.867435	0.025721	0.024675	0.063965	0.032966	0.022026	0.023208	0.001348
Contempt	0.023721	0.893439	0.014651	0.043965	0.032966	0.042026	0.023208	0.023965
Disgust	0.025713	0.024679	0.917439	0.013965	0.036766	0.012026	0.023208	0.043765
Fear	0.037659	0.042766	0.024151	0.934579	0.004675	0.046751	0.014675	0.024675
Happy	0.036766	0.063965	0.014671	0.04675	0.907436	0.023965	0.063965	0.023965
Neutral	0.036766	0.024675	0.016751	0.013575	0.012346	0.907438	0.023965	0.016786
Sadness	0.036766	0.014454	0.06395	0.056654	0.063965	0.017464	0.947438	0.023751
Surprise	0.036766	0.014651	0.076325	0.034567	0.034568	0.038765	0.097834	0.927438

Table 3.
CONFUSION MATRIX (CNN MODEL)

Emotion	Anger	Contempt	Disgust	Fear	Happy	Neutral	Sadness	Surprise
Anger	0.867435	0.02572064	0.0246751	0.063965	0.032966	0.022026	0.023208	0.0013475
Contempt	0.023721	0.89343946	0.0146507	0.043965	0.032966	0.042026	0.023208	0.023965
Disgust	0.025713	0.02467507	0.9174391	0.013965	0.036766	0.012026	0.023208	0.043765
Fear	0.037659	0.04276585	0.0241507	0.934579	0.004675	0.046751	0.014675	0.024675
Happy	0.036766	0.06396496	0.0146707	0.04675	0.907438	0.023965	0.063965	0.023965
Neutral	0.036766	0.02467507	0.0167507	0.013575	0.012346	0.907438	0.017464	0.038765
Sadness	0.036766	0.01445361	0.0639496	0.056654	0.063965	0.017464	0.947438	0.097834
Surprise	0.036766	0.0146507	0.0763245	0.034567	0.034568	0.038765	0.097834	0.927438

Table 2, Table 3 and Figure 10 give the recognition results in the form of confusion matrix. The smooth threshold method suggested is used. For studies, tenfold cross validation is used. The use of the suggested smooth threshold technique in each production node increases the identification efficiency. When hard limit is implemented, a median accuracy of acceptance of 86.74 is accomplished. The accuracy of the detection is 97.74 percent for the implementation of the gentle threshold, which improve considerably. CNN and SVM expend fewer training time and reach a strong identification rate in tandem with the standard. The CK+ and MMI dataset dependent tests validate the system's benefit. A high accuracy of over 90% can be obtained by state-of-the-art Facial Expression Recognition approaches (Elizabeth, 2020) (Moore S., 2011) on MMI (Pantic M. V., 2005) and CK+ (Kanade, 2010) data sets. In light of the early samples of pose-invariant facial expressions with limited face occlusion, MMI (Pantic M. V., 2005) and CK+ (Kanade, 2010) and Google databases have tested the bulk of the approaches to FER. And the FER benchmark is commonly used for these two data sets. FER methods are typically less than 80 per cent reliable for MMI (Pantic M. V., 2005) data sets. Due to the standard appearances and clothing of the subjects (e.g., mirror, moustache) there are major interpersonal differences. Experiences with 8 FER methods reveal that the MMI data set performs superior deeper learning methods with an improvement in precision of 10%.

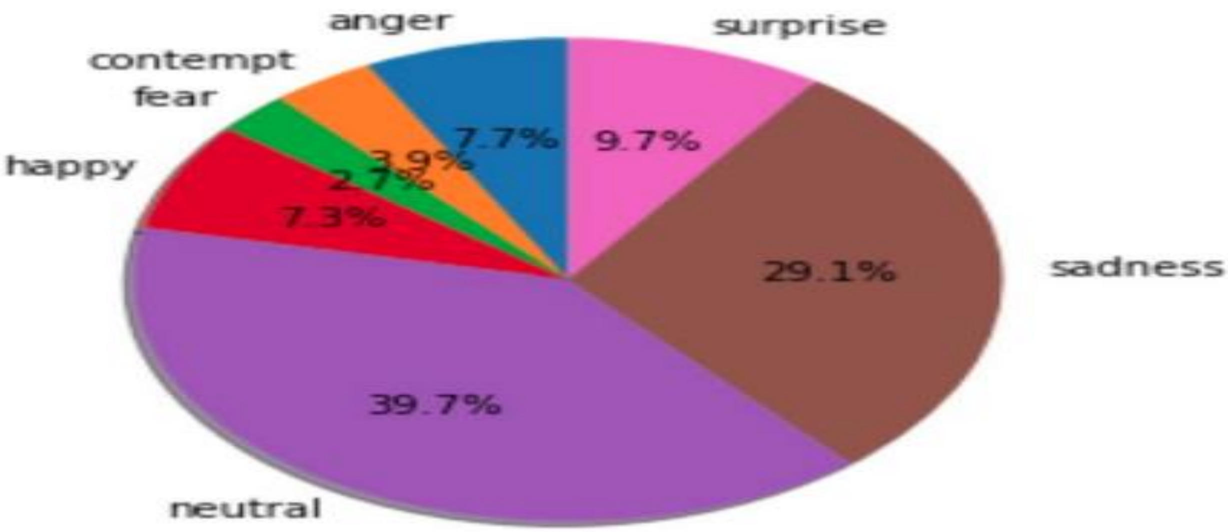

Figure 1.
Basic Emotions Calculated in Percentage

By contrasting our proposed research provides better overall better results. The researcher is problematically based and can only verify that category performs best on facial picture data set. The findings are also analyzed. The best approach for Classifier ensemble is not to test the perfect classifier but to select the best outcomes of its own (Shahid M. A., 2024) (Shahid M. A., 2018) (Shahid M. A., 2025). No doubt further optimization techniques such as Haar cascade algorithm can significantly reduce error in order to achieve the overall system performance. The maximum accuracy of each classification with SVM classification is 83.15% while the maximum Accuracy by CNN model created is measuring it by 94.02%. Table 4 shows the accuracy of each data set classification and expression.

Table 4.
ACCURACY AND DATA SET OF EACH CLASSIFICATION

Data Sets	Happy	Angry	Disgusted	Fear	Surprise	Contempt	Sad
CK+	96.30%	97.18%	96.00%	100%	91.67%	98.39%	97.41%
MMI	76.67%	79.72%	75.23%	90.92%	82.56%	83.44%	59.23%
Google Dataset	77.65%	72.33%	82.05%	96.32%	79.55%	83.30%	89.80%

CONCLUSIONS

In current research, a framework has been proposed towards evaluation of approaches and techniques for having emotional sentiments in learning environment over edge-based infrastructure. The analysis of Facial Action Units has capacity of measuring effective multi pose face expression recognition in real time. It improves the amount of facial extraction and leads to elevated precision of identification through kernel trick SVM classifier and CNN. The algorithm achieved competitive accuracy between 84%

and 94%. Almost anything can be assessed, but whether the assessment is accurate, realistic and true is of concern. Facial recognition systems are not always accurate, and their performance can be affected by factors such as lighting conditions, facial expressions, and camera angles. Moreover, these systems have been shown to exhibit bias, particularly in their performance across different racial, ethnic, and gender groups. This bias can lead to unequal judgement and need to be catered by domain experts and instructors. Moreover, conducting thorough testing, implementing ethical guidelines, involving diverse stakeholders, and collaborating with regulatory bodies to ensure that the technology is used responsibly and respects individual rights and privacy.

The potential future endeavors may target to fine tune the model established. Categorization and identification of further sub emotions may assist in simplifying the research outcomes. The research may also consider the usage of deep-learning methods gesture analysis for precise spectator feedback to simplify the time complexities involved over edge-based devices. Moreover, a gesture analysis for deep analysis of speaker and audience may be considered for advancement in domain of emotions measurement.

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Conflicts of Interests: The authors declare no conflict of interest.
Consent to Participate: Yes
Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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