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Emotion Based Facial Expression Detection Using Machine Learning

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Abstract: Humans have the capability to deliver many emotions during a conversation. Facial expressions show information about emotions. The major issue is to understand the facial expression during communication. Every face is an index of the mind. The objective of this study is to design a framework which has the ability to recognize human facial expression. Permanent and temporary facial expressions appear during conversation and detect using different face detection techniques. In this study, an emotion-based face identification system has been proposed by employing different machine learning approaches. Taiwanese Facial Expression Image Database (TFEID) has been used for three types of facial expression such as Angry, Happy and Sad. Each facial expression (Angry, Happy and Sad) contains 40 images and calculate total 120 (40 x 3) images dataset. For image pre-processing, Median filter has been employed on this dataset and converted color images to gray scale. Six non-overlapping regions of interest (ROIs) have been taken on every image and calculate 720 (120 x 6) ROIs on the overall dataset. Texture (T), Histogram (H) and Binary (B) features have been calculated on these three categories and extracted 43 features on each (ROIs) and calculated total 30960 (720 x 43) features vector pace on the deployed dataset. The Best First Search (BFS) algorithm has been implemented for feature optimization. The optimized dataset has been deployed to different machine learning classifiers namely Meta Random Sub Space, Meta Random Committee, Meta Bagging, Random Forest Tree, J48 Tree, and LMT Tree. Tree Random Forest has shown the best overall accuracy results among the deployed classifiers. The overall accuracy result of 95.277% has been observed by Tree Random Forest.
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Key Words: Texture, Histogram and Binary Features.

1. Introduction

Message has been given importance in human life. A complete message can be transferred in two different ways verbal and non-verbal. Non-verbal message are exchange by different ways, such as face gestures and movement of body. Every day human beings perform different facial gestures during communication.

Facial expression is a main part of non-verbal communication; because facial gesture has major part to explain human actions [1]. Facial expression data has been distributed in different segments to get desired information that has deployed in different computer vision approaches. The area of eyes, nose, lips and chin are changed during conversation.

Many issues have been faced during facial expression due to dynamic movement of face recognition. Thus many problems have been faced during collection of facial dataset such as eyes, nose, lips, and chin etc. The overall accuracy is 90% on the basis of RST-Invariant and Texture features with K-Nearest Neighbor (KNN) algorithms [2].

Different machine learning approaches have been used for face recognition techniques. It also helps us to understand the emotion, mindset and behavior of human. Face muscles allow us to get useful information about face gestures. Human Computer Interaction (HCI) and Computer Interaction have been used in computational model to achieve better results on the following expression such as Happiness 99%, Surprise and Disgust 95%, Sadness 90%, Anger 94% and Fear 92% [3].

Automated facial expressions methods have been faced different challenges in face detection process. To describe the classification problems of single community facial expression dataset is easy as.

compared to Multi Community data set. Deep Neural Network (DNN) architecture achieve better result on multiple database namely MultiPIE 94.8%, MMI 56.0%, CK+ 92.2%, DISFA 56.1%, FERA 77.4%, SFEW 48.6% and FER2013 61.1%[4].

Shape Modeling (Mark Feature Points, Align Shape of Images, Establish Shape Model) and Texture Modeling (Map, Establish Texture Model) parameter have been express more information facial expression. A statistical Active Appearance Model (AAM) is used for three experimental procedures. AAM model achieved better result on experiment-1, 97.5%, experiment-2, 98.5% and experiment-3, 92.50% [5].

Edge Detection algorithms are based into two types: statistically and knowledge based method. Eyes and lips area are shown variation during human communication. Canny, Laplace, Sobeland Robert edge detection filters have been used in imaging processing. Canny Edge Detection (CED) provide better results on following facial expressions such as Normal 100%, Sad 91.3%, Smile 99.4% and Surprise 95.7% [6].

Automated and semi-automated facial expression techniques having been getting popularity due to growing up human computer interaction. Facial Action Coding System (FACS) has been applied on BP4D and SEMAINE facial expression databases which have been achieved better results on the basis of Geometrics and appearance features [7].

Transductive Parameter Transfer (TPT) has been used to develop personalized classification model. The main purpose of TPT model has been used to pre-trained regression function and computational cost, which is much lower than other algorithms. Human Computer Interaction (HCI) is based on facial expression. Gesture recognition technologies are evaluated by different classification approaches. TPT get better output on the basis of PAINFUL 78.3% and CK+ database 92.7% [8].

Emotions have different salient features in facial expression. Patch Matching Operation technique is helpful for extract these salient areas features. Patch Based Gabor features has performed better results on the basis of JAFEE and CK+ database and acquired overall accuracy (OA) 92.93% and 94.48% [9].

Face recognition system is user friendly in human computer interaction. Particular person identify through network access control via face recognition techniques [10].

Live video streaming data have been used for experimental process. Different classifier techniques implemented and observed OA by expert user 87.5% [11]. Boosted Neural Network Ensemble (BNNE) classified with multicultural dataset and achieved better results 81.73%, 92.79 % and 90.63% by using LBP, HOG and PCA features respectively. JAFFE, TFEID and RadBoud database have been used for experimental work [12].

2. Image Dataset

In this study, Taiwan Facial Expression Images Database (TFEID) is benchmark dataset which has been selected for experimental work and was established by the Brain Mapping Laboratory (National Yang-Ming University) and Integrated Brain Research Unit (Taipet Veterans General Hospital). Eight different types of facial expressions have been used in TFEID, such as Neutral, Anger, Contempt, Disgust, Fear, Happiness, Sadness and Surprise [13]. Every facial expression dataset has natural because human facial expression has been real all over the community. Three categories of TFEID database namely Angry (A), Happy (H) and Sad (S) have been used for experimental work which is shown in figure 1.

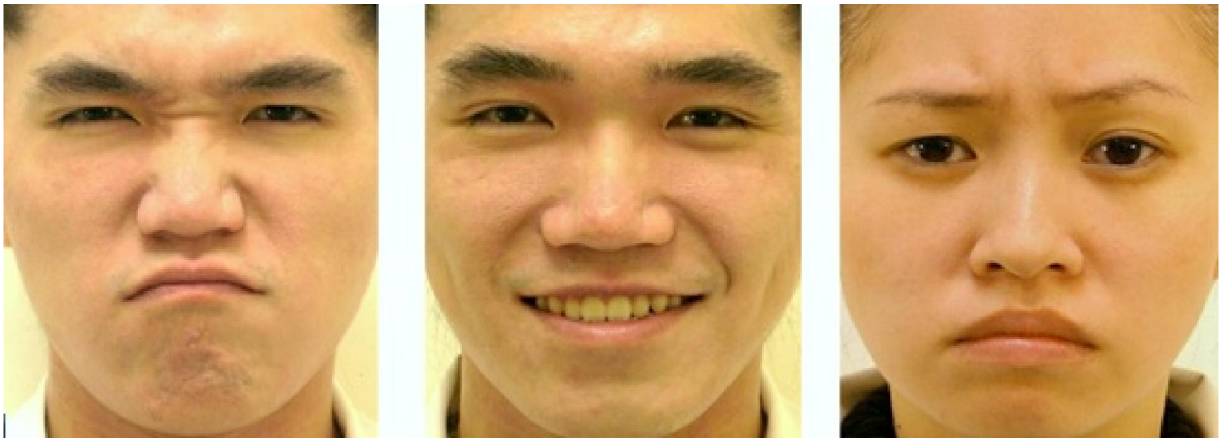
The image resolution of size 460 x 600 pixels and 24 bit depth which from Joint Photographic Expert Group (JPEG) format. Face identification and images adjustment technique report in [14], which explain better approach for face capturing. Facial expression has been containing 40 images (19 Male, 21 Female) dataset without whiskers, moustaches, glasses and face coloring. Facial images have been capture with digital photographic and highly resolution digital Charged Coupled Device (CCD) camera.

3. Research Methodology

In this study different procedural steps have been implemented for image processing, ROIs selection, feature extraction and classifiers. Different machine learning tools implemented for image processing, that's CVIP and WEKA software (Version 3.8.1) on Intel (R) core i3 processor 2.4Giga Hertz (GHz), 2 GB RAM and 64-bit window 7 operating system [15]. A proposed facial expression algorithm has been described given below.

Proposed Algorithm:

Proposed algorithm explains with all necessary steps.



A (Angry) **B (Happy)** **C (Sad)**

Figure 1: Image Data set [13]

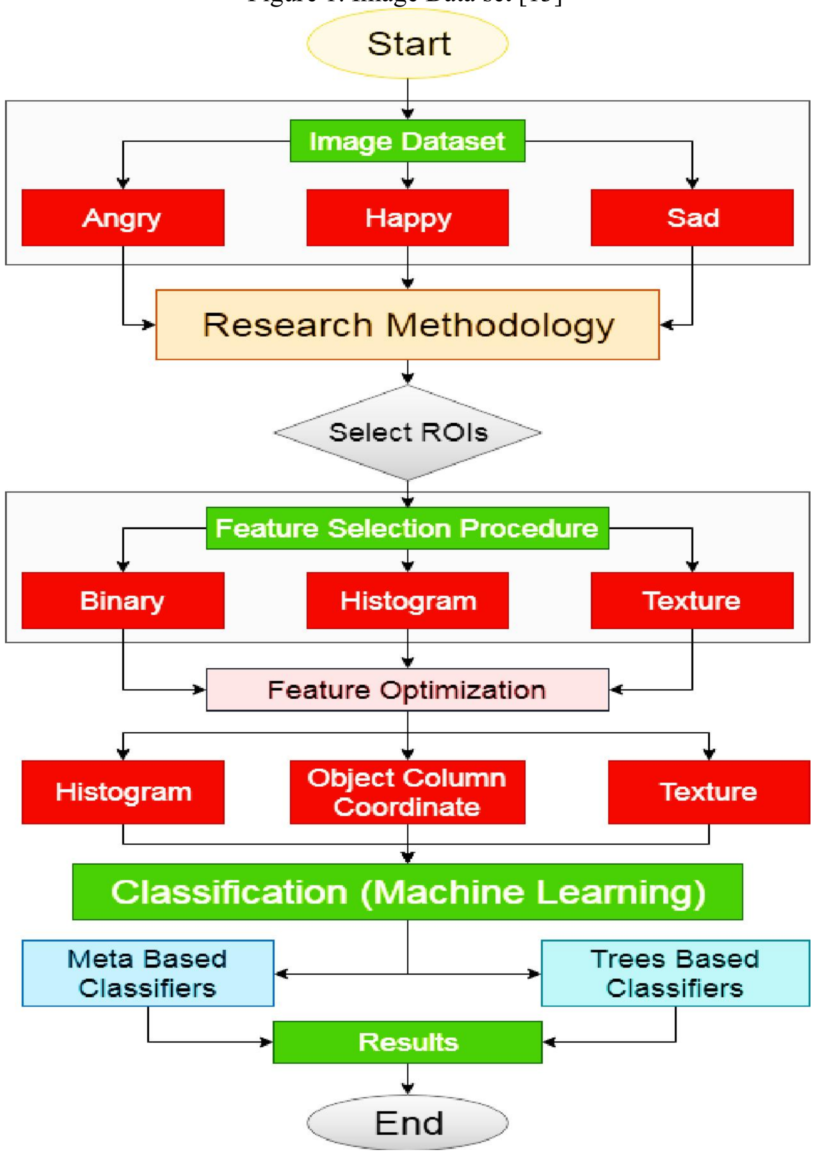


Figure 2: Proposed Framework for Facial Expression Identification

Proposed Algorithm

Start main ( )
{
Input → facial image expression dataset
For
{
Stage 1 to stage 5
Stage 1 → Three types of images (A, H, S) dataset.
Stage 2 → Preprocess of dataset.
Stage3 → ROIs for feature extraction.
Stage 4 → Extract 43 (B + H + T) features.
Stage 5 → Feature Optimization
End For
}
Stage 6 → Machine learning classification.
Output → Facial expression results.
End main
}

The identification framework of facial expression has been described in figure 2.

In first stage collect three different (Angry, Happy and Sad) categories of facial expression. Second stage has describe detail description of preprocess techniques and research methodology. In this stage images have been resize 512 x 512 pixels. All images dataset has been arranged in separate file for further image processing. In stage three, that is create 6 non overlapping ROI'S on each image for feature extraction. The accuracy of results on d=2 (d=distance) pixel.

In stage four, different feature Binary (B), Histogram (H) and Texture (T) techniques have been implemented for feature selection procedure and extract 43 (28 Binary, 10 Histogram and 5 Texture) features. In stage five, BFS algorithm deployed for feature optimization. It has been observed that following features are Histogram Mean (HM), Histogram Entropy (HE), Texture Energy (TE), Texture Inverse_diff_average (TIA) and Object Column Coordinates provide better results from available dataset.

In stage six, calculate different classifier namely Meta (Random Sub Space, Meta Random Committee, Meta Bagging) and Trees (Random Forest, J48 and LMT Tree).

The main purpose of this study is to identify the facial expression by using Machine Learning (ML) techniques.

3.1 Image Preprocessing

Face recognition has been employed preprocessing techniques on photographic data for eliminating noisy and irrelevant information. The variation in facial expression has different factors such as age, ethnicity, community and gender. The first step has to convert the images color to gray scale. Median filters are deployed for image preprocessing steps; these images are become more appropriate for further processing.

The next step has to create preprocessing non overlapping ROIs on each image. Every image has been converted into (480 x 600) to (512 x 512) pixel resolution and taken 6 non overlapping ROIs on each image in figure 3 [13]. The total dataset 120 (40 x 3) images on three categories of facial expression have been taken before experimental process. The overall selected ROIs 720 (120 x 6) of each category.

Figure 3: Selected 6 Non Overlapping ROI's Image [13]

4. Feature Selection Procedure

Many researchers have been implemented different techniques for feature extraction [2], [16], [17]. The accuracy in classification task from a huge dataset has been depending on feature selection that is why feature selection procedure play very important role in image processing. In this study B, H and T features have been extracted. Statically measurement of feature selection B, H and T are discussed given below:

Binary Feature:

Binary features identify the objects and shape of the object in image processing on the basis of Area, Axis of least second moments, Euler number, center of area and projection.

Histogram Feature:

A histogram consists of a set of adjacent rectangles having bases along the X-axis with centers at the class marks and areas proportional to the class frequency. Histogram shapes have been calculated the information about image on the basis of gray level and number of pixel. The first order histogram probability P (h) as follows in equation 1.

$$P(h) = \frac{K(h)}{N} \quad (1)$$

Here N is total pixel in the image and K (h) is total pixel at gray level of h.

The first order histogram probability are used following method that are Mean, Standard Deviation, Skewnees, Energy and Entropy for statistical calculation.

Mean is average values, it describe the bright (High Mean) and dark (Low Mean) image. Mean define as follow in equation 2.

$$\bar{h} = \sum_{h=0}^{P-1} hP(h) = \sum_{x}\sum_{y}\frac{I(x,y)}{N} \quad (2)$$

P is the total number of gray levels that's range 0 to 255. The corresponding values of x (Rows) and y (Colum's) represent the pixel.

Standard deviation (SD) describes the contrast of image. SD defines as follows in equation 3.

$$\boldsymbol{\sigma_h = \sqrt{\sum_{h=0}^{P-1}(h-\bar{h})^2 P(h)} \quad (3)}$$

Skewness (Skew) is the lack of symmetry in a distribution around some central values (Mean, Median, Mode). It is the degree of asymmetry. The frequency curve has distributed into longer tail to right (Positive) and longer tail to left (Negative). Skew define as follows in equation 4.

$$\mathbf{Skew} = \frac{1}{\sigma_h^3}\sum_{h=0}^{P-1}(h-\bar{h})^3 P(h) \quad (4)$$

Energy is measured the distribution of gray levels that define in equation 5.

$$\mathbf{Energy} = \sum_{h=0}^{P-1}[P(h)]^2 \quad (5)$$

Entropy is measured the total number of bits are required to code the image data is define in equation 6.

$$\mathbf{Entropy} = -\sum_{h=0}^{P-1} P(h)\log_2[P(h)] \quad (6)$$

Texture Feature:

The object of image is selecting by row and column coordinates in texture. Texture has been calculated on five different methods that are energy, correlation, entropy, inverse difference and inertia.

Energy evaluated smoothness or homogeneity by calculating the distribution between gray levels are define in equation 7.

$$\mathbf{Energy} = \sum_{m}\sum_{n}(C_{mn})^2 \quad (7)$$

Here C_{mn} are the values in the co-occurrence matrix by distribution values of pixel.

Correlation method is defining the similarity of pixel at specified pixel distance. Correlations method defines as follows in equation 8.

$$\mathbf{Correlation} = \frac{1}{\sigma_a\sigma_b}\sum_{m}\sum_{n}(m-\mu_a)(n-\mu_b)C_{mn} \quad (8)$$

Here μ_a **and** μ_b are the means of a and b respectively.

$$\mu_a = \sum_m m \sum_n C_{mn} \quad (8.1)$$
$$\mu_b = \sum_n n \sum_m C_{mn} \quad (8.2)$$
$$\sigma_a^2 = \sum_{m}(m-\mu_a)^2\sum_{n}C_{mn} \quad (8.3)$$
$$\sigma_b^2 = \sum_{n}(n-\mu_b)^2\sum_{m}C_{mn} \quad (8.4)$$

Gray level co-occurrence matrix or Gray level dependency matrix are measured by second order histogram method with distance and angle parameters.

Entropy is measure the content information of image. Entropy defines as follow in equation 9.

$$\mathbf{Entropy} = -\sum_{m}\sum_{n}C_{mn}\log_2 C_{mn} \quad (9)$$

Inverse difference method is measure the local homogeneity of image that defines as follow in equation10.

$$\mathbf{Inverse\ Difference} = \sum_{m}\sum_{n}\frac{C_{mn}}{|m-n|} \quad (10)$$

Inertia method is measure the contrast that defines as follow in equation 11.

$$\mathbf{Inertia} = \sum_{m}\sum_{n}(m-n)^2 C_{mm} \quad (11)$$

As above discuss the available 43 features (Binary + Histogram + Texture) have been calculated for each ROIs. It has been calculate total 30960 (43 x 720) features on the basis of available image dataset.

5. Classification

Best First Search (BFS) algorithm filters are used for feature optimization. The accuracy of results is better on the basis of Histogram (HM and HE), Texture (TE and TIA) and Object Column Coordination through employing different machine learning classifier namely Meta Random Sub Space, Meta Random Committee, Meta Bagging, Random Forest Tree, J48 Tree and LMT Tree.

6. Results

Experimental results describe on facial

expression dataset such as Angry, Happy and Sad. The description of following dataset is given in table 1.

Different tuning parameters have been calculated to measure the efficiency of these image dataset that are Mean Absolute Error (MEA), Root Mean Square Error (RMSE), True Positive (TP), False Positive (FP), Receiver Operating Characteristics (ROC), Time Complexity Factor (TCF), Total number of Instances (TNI) and Overall Accuracy (OA) have also been calculated and given formulas explain these tuning parameters equation are shown given below [16].

Table 1: Description of Facial Dataset

Database	**Category**	**No. of Images**	**Type of Emotion**
TFEID (Taiwanese)	57 Male 63 Female	120	Angry Happy Sad

TP Rate = TP / (TP+FN) (12)
TN Rate = TN / (TN+FP) (13)
FP Rate = FP / (FP+TN) (14)
FN Rate = FN / (FN+TP) (15)

Accuracy = (TP + TN) / (TP + FP + FN+TN) (16)

In first step, multi features based dataset for facial expressions have been implemented by different machine learning classifiers which are shown in Table 2 and Table 4.

Meta based machine learning classifiers namely Random Sub Space, Bagging and Random Committee have been deployed but Meta Random Committee gives better result 93.1944% as compared to Random Sub Space 92.222% and Bagging 90.1389% is given in Table2.

The confusion matrix of Meta Random Committee based classifier has shown in given Table 3. The maximum values diagonally are shown which are placed in three different facial expression classes [15].

It has been observed that Meta based classifier result were not so impressive, this is the reason a Tree based machine learning classifiers namely Random Forest, J48 and LMT Tree have been deployed but Tree Random Forest gives better result 95.277% as compared to LMT Tree 91.111% and J48 Tree 90.833% is given in Table 4.

Table 2: Meta Based Classification Results

Meta Classifiers	**Kappa Statistics**	**TP Rate**	**FP Rate**	**ROC**	**MAE**	**RMSE**	**TNI**	**Time (sec)**	**OA**
Random Committee	0.8979	0.932	0.034	0.982	0.0643	0.1745	720	0.07	93.194%
Random Sub Space	0.8833	0.922	0.039	0.980	0.1427	0.228	720	0.08	92.222%
Bagging	0.8521	0.901	0.049	0.979	0.1275	0.2265	720	0.13	90.138%

Table 3: Confusion Matrix for Meta Random Committee Classifier

Classes	**Angry**	**Happy**	**Sad**
Angry	**216**	23	1
Happy	25	**215**	0
Sad	0	0	**240**

Table 4: Tree Based Classification Results

Meta Classifiers	**Kappa Statistics**	**TP Rate**	**FP Rate**	**ROC**	**MAE**	**RMSE**	**TNI**	**Time (sec)**	**OA**
Random Forest	0.9292	0.953	0.024	0.929	0.1006	0.1825	720	0.27	95.277%
LMT	0.8667	0.911	0.044	0.960	0.0625	0.2352	720	2.77	91.111%
J48	0.8625	0.908	0.046	0.938	0.0696	0.2432	720	0.28	90.8333%

The confusion matrix of Tree Random Forest based classifier has shown in given Table 5. The maximum values diagonally are shown which are placed in three different facial expression classes.

A confusion matrix comparison graph between Meta Random Committee and Tree Random Forest has been shown in figure 4.

Table 5: Confusion Matrix for Tree Random Forest Classifier

Classes	Angry	Happy	Sad
Angry	**218**	20	2
Happy	12	**228**	0
Sad	0	0	**240**

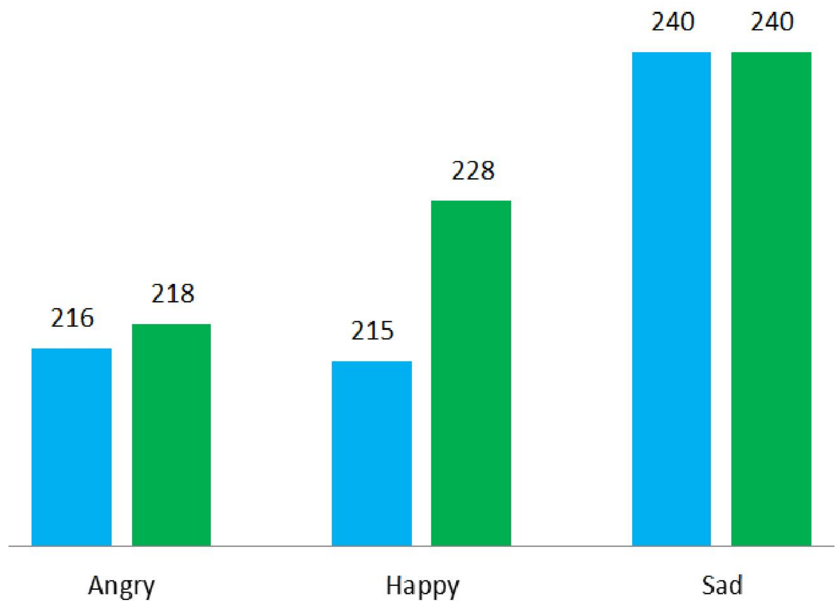


Figure 4: Confusion Matrix Comparison Graph of Tree Random Forest and Meta Random Committee Classifiers
Dataset (Meta Random Committee Classifier)
Dataset (Random Forest Tree Classifier)

Facial expression classification graph of Tree Random Forest and Meta Random Committee has shown in figure 5[16].

Tree Random Forest classifier has shown better overall accuracy is 95.277% as compared all other classifiers. A comparison between proposed and existing approach has shown in given table 6.

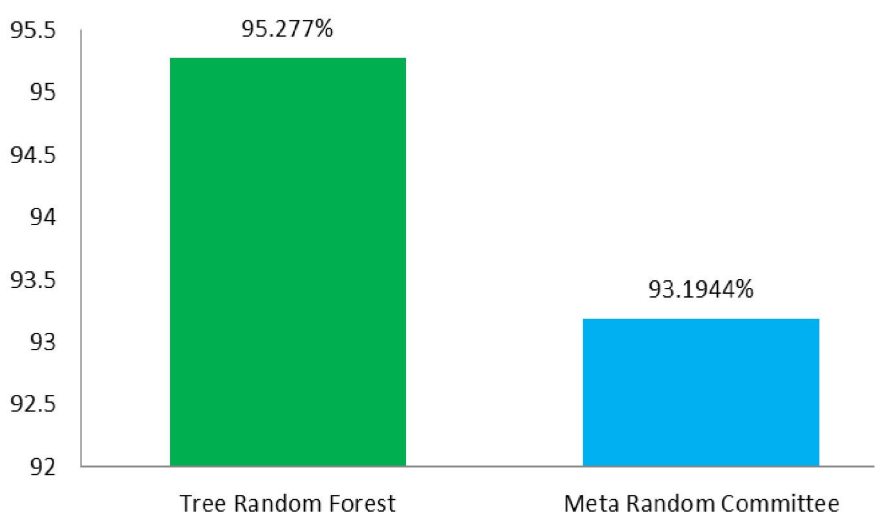


Figure 5: Comparison Graph of Meta Random Committee and Tree Random Forest Classifier
Dataset (Meta Random Committee)
Dataset (Random Forest Tree)

Table 6: Comparison with Proposed and Existing Approach

Ref. No	Database	Classifier / Algorithm's	Features	OA
[2]	Static Real Image	K – Nearest Neighbor	RST – Invariant and Texture	90%
[4]	CK+ & MultiPIE	DNN	SVM and KNN	92.2% & 94.8%
[8]	PAINFUL and CK+	TPT and SVM	Texture	78.3% & 92.7%
[9]	JAFEE and CK+	Patch Matching	Gabor	92.93% & 94.48%
[12]	TFEID	Boosted NNE	LBP, HOG and PCA	92.79%
Proposed Approach	TFEID	Tree Random Forest	Binary, Histogram and Texture	95.277%

Conclusion:

In this study, the TFEID database has been used to classify the three facial expressions that are Angry, Happy and Sad. To remove the anomalies, different image preprocessing steps have been used that are image resizing and color to gray level. Three types of features Binary, Histogram and Texture have been extracted. These features have been deployed to Trees and Meta based machine learning classifiers.

A comparison results have been observed between these two types of machine learning classifiers. Finally Tree (Random Forest) classifier has shown better result 95.277% as compared to Meta (Random Committee) 93.1944%classifiers.

Future Work:

In future fusion based facial expression methods will be used to get better accuracy results.

Author Contribution:

The main idea and implementation (experimental) procedure were performed by Tanveer Aslam and Dr. Salman Qadri made critical revision and approved the final version.

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References:

1 Paul Ekman and Wallace V. Friesen, *Unmasking The Face*. Cambridge USA: MALOR BOOKS, 2003.

2 Nazia Perveen, Nazir Ahmad, Muhammad Abdul Qadoos Bilal Khan, Rizwan Khalid, and Salman Qadri, "Facial Expression Recognition Through Machine Learing," *INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH*, pp. 91-97, March 2016.

3 Aleix Martinez and Shichuan Du, "A Model of the Perception of Facial Expressions of Emotion by Humans: Research Overview and Perspectives," *Journal of Machine Learning Research*, pp. 1589-1608, 2012.

4 Ali Mollahosseini, David Chan, and Mohammad H. Mahoor, "Going Deeper in Facial Expression Recognition using Deep Neural Networks," in *WACV 2016: IEEE Winter Conference on Application of Computer Vision*, Lake Placid NY USA, 2016, pp. 1-10.

5 Wenchao Zheng and Cuicui Liu, "Facial Expression Recognition Based On Texture And Shape," in *2016 25th Wireless and Optical Communication Conference (WOCC)*, Chengdu, China, 21-23 May 2016, pp. 1-5.

6 Xiaoming CHEN and Wushan CHENG, "FACIAL EXPRESSION RECOGNITION BASED ON EDGE DETECTION," *International Journal of Computer Science & Engineering Survey (IJCSES)*, vol. 6, no. 2015, pp. 1-9, April 2015.

7 Michel F. Valstar, Timur Almaev, Jeffrey M. Girard, Gary McKeown, and Marc Mehu, "FERA 2015 - Second Facial Expression Recognition and Analysis Challenge," in *2015 11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, Ljubljana Slovenia, 2015, pp. 1-9.

8 Gloria Zen, Lorenzo Porzi, Enver Sangineto, Elisa Ricci, and Nicu Sebe, "Learning Personalized Models for Facial Expression Analysis and Gesture Recognition," in *IEEE TRANSACTIONS ON MULTIMEDIA*, APRIL 2016, pp. 775-787.

9 Ligang Zhang, Student Member IEEE, and Dian Tjondronegoro, "Facial Expression Recognition Using Facial Movement Features," in *IEEE TRANSACTIONS ON AFFECTIVE*

COMPUTING, 2011, pp. 219-229.
10 Shang-Hung Lin, "An Introduction to Face Recognition Technology," *Information Science Special Issue on Multimedia Information Technologies*, pp. 1-7, 2000.
11 Philipp Michel and El Rana Kaliouby, "Real Time Facial Expression Recognition in Video using Support Vector Machines," in *The Fifth International Conference on Multimodal Interfaces (ICMI-PUI'03)*, Vancouver B.C. Canada, 2003, pp. 1-7.
12 Ghulam Ali, Amjad Muhammad Iqbal, and Tae-Sun Choi, "Boosted NNE Collections for Multicultural Facial Expression Recognition," *Pattern Recognition*, p. Elsevier Ltd, July 2016.
13 Brain Mapping Laboratory and Brain Research Unit. TFEID (Taiwanese Facial Expression Image Database). [Online]. http://bml.ym.edu.tw/tfeid/
14 Li Chen, Jin-Guo Zhang, Hai-Feng Su, and Wei Guo, "Weed Identification Method Based on Probabilistic Neural Network in the Corn Seedlings Field," in *2010 International Conference on Machine Learning and Cybernetics*, Qingdao China, 2010, pp. 1-4.
15 Salman Qadri, Dost Muhammad Khan, Syed Furqan Qadri, Muzammil Ul Rehman, and Mutiullah, "A Novel Optimized Land Cover Classification Framework Using Data Mining Techniques," *Sindh University Research Journal (Science Series)*, pp. 433-440, May 2017.
16 Salman Qadri et al., "Multisource Data Fusion Framework for Land Use/Land Cover Classification Using Machine Vision," *Hindawi Journal of Sensors*, pp. 1-8, September 2017.
17 Zhen-Tao Liu, Gui-Tian Sui, Dan-Yun Li, and Guan-Zheng Tan, "A Novel Facial Expression Recognition Method Based on Extreme Learning Machine," in *Proceedings of the 34th Chinese Control Conference*, Hangzhou China, July 28-30, 2015, pp. 3852-3857.
18 Zhengyou Zhang, "Feature-Based Facial Expression Recognition: Sensitivity Analysis and Experiments With a Multi-Layer Perceptron," *International Journal of Pattern Recognition and Artificial Interlligence (IJPRAI)*, pp. 893-911, 1999.
19 Marian Stewart Bartlett, Gwen Littlewort, Claudia Lainscsek, Ian Fasel, and Javier Movellan, "Machine Learning Methods for Fully Automatic Recognition of Facial Expressions and Facial Actions," in *2004 IEEE International Conference on Systems, Man and Cybernetics*, 2004, pp. 592-597.
20 Charles A. Nelson, "The Development and Neural Bases of Face Recognition," USA, 2001.
21 Robert M. Haralick, K. Shanmugam, and Its'HAK Dinstein, "Textural Features for Image Classification," *IEEE Transactions On System, Man and Cybernetics*, pp. 610-621, November, 1973.
22 Majid Mirmehdi, Xianghua Xie, and Jasjit Suri, *HANDBOOK OF TEXTURE ANALYSIS*. Covent Garden London: Imperial College Press.
23 Andre Teixeira Lopes, Edilson de Aguiar, and Thiago Oliveira Santos, "A Facial Expression Recognition System Using Convolutional Networks," in *28th SIBGRAPI Conference on Graphics, Patterns and Images*, 2015, pp. 273-280.
24 Yongqiang Li, Shangfei Wang, Member IEEE, Yongping Zhao, and Qiang Ji, "Simultaneous Facial Feature Tracking and Facial Expression Recognition," in *IEEE TRANSACTIONS ON IMAGE PROCESSING*, July, 2013, pp. 2559-2573.
25 Paul Viola and Michael Jones, "Rapid Object Detection using a Boosted Cascade of Simple," in *ACCEPTED CONFERENCE ON COMPUTER VI SI ON AND PATTERN RECOGNI TI ON 2001*, 2001, pp. 1-9.
26 Carlos Busso et al., "Analysis of Emotion Recognition using Facial Expressions, Speech and Multimodal Information," in *ICMI'04*, Pennsylvania USA, October 13–15, 2004, pp. 205-211.
27 Fernando de Almeida Freitas and Sarajane Marques Peres, "Grammatical Facial Expressions Recognition with Machine Learning," in *Proceedings of the Twenty-Seventh International Florida Artificial Intelligence Research Society Conference*, 2014, pp. 180-185.
28 Dr. Scott E Umbaugh, *DIGITAL IMAGE PROCESSING AND ANALYSIS Human and Computer Vision Applications with CVIPtools (SECOND EDITION)*. Boca Raton and New York: CRC Press Taylor & Francis Group LLC, 2010.

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