International Journal of Applied Mathematics
Volume 38 No. 5s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

A HYBRID DATA MERGING AND AUGMENTATION-BASED DEEP FRAMEWORK FOR NEGATIVE AFFECT DETECTION

Suja Sreejith Panicker, P. Gayathri*

SCOPE, Vellore Institute of Technology, Vellore,

Tamil Nadu, India

*suja.panicker2017@vitstudent.ac.in, pgayathri@vit.ac.in**

Abstract

Emotion Recognition (ER) refers to capturing the different aspects pertaining to detection of emotions. Performance of ER models is hindered by several challenges including lack of generalization. The latter is influenced by factors including class imbalance, intra-domain differences, occlusions, varied image sizes and dimensionality of datasets. While Data Augmentation (DA) remains a prevailing solution, there is a pressing need for large, balanced, and heterogeneous datasets representing diverse real-world scenarios. Additionally, there is lack of comprehensive framework to combine augmentation and merging, particularly for applications in mental health. To address these issues, we propose a Recommendations and Behavioural support-based Framework for Negative Affect detection (RBF-NA). At the core of RBF-NA, we introduce an interesting pipeline, the Hybrid-Multi Stage Augmentation and Merging (H-MSAM). This pipeline is supported by introducing a novel algorithm AG-L1. Furthermore, a custom deep model for emotion detection, the Convolutional-Face Emotion Detection (C-FED) is proposed. C-FED achieves exceptional performance with highest accuracies of 99.75% on CK+ and 85.87% on KDEF datasets. H-MSAM improves the accuracy by 13.31%, 16.96%, and 19.44% on CK+, KDEF, and FER2013, respectively. Furthermore, C-FED outperforms ResNet and VGG16, with accuracy gains of 6.87% and 5.13%, respectively. The granular performance of system demonstrates excellent performance on every emotion class, with the negative emotions including sad, angry achieving superior results. The promising findings in this paper highlight the potential of RBF-NA in advancing ER research and fostering early detection of negative emotions.

Keywords: Computer Vision, Artificial Intelligence, Deep Learning, Affective Computing, Data Augmentation, Mental Health, Facial Emotion Recognition, Healthcare.

1. Introduction

Affect is a complex, multidimensional concept that embodies the dynamic interplay between positive and negative emotional experiences [1]. In healthcare the study of affect is crucial due to its impact on cognitive processes, decision-making, and behavioral outcomes. Affect may be delineated into two categories, positive or negative. Positive affect refers to a psychological state marked by the experience of positive emotions including joy, excitement, and happiness. Negative affect is often characterized by emotions of sadness, anxiety, anger,

Received: August 09, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

or frustration [2]. The prominent review by Panicker et al. [3] suggests that persistent negative emotions may progressively lead to significant mental health issues and severe outcomes including suicide (especially in the case of adolescents). World Health statistics by Bertuccio et al. [4] indicate that more than one per 100 deaths globally is attributed to suicides. These figures highlight the necessity for a robust AI-powered Negative Affect monitoring system.

Various modalities can be employed to identify and analyze human emotional states. Facial expressions are the most popular and serve as an immediate indicator of affective experiences, often transcending linguistic barriers and enhancing interpersonal understanding. Facial expressions convey emotional states, personality traits, as well as psychiatric and medical conditions. The detection and recognition of facial emotions is popularly known as Facial Emotion Recognition (FER) [5], and is an interesting sub-field in Affect Detection.

1.1 Motivation

1. There is compelling need for a comprehensive system that emphasizes negative affect detection. This system would be incomplete without customized recommendations for behavioral-support. Facial expressions are fundamental in nonverbal communication. Hence, developing a robust FER system is instrumental for societal well-being owing to its timely and effective detection of emotions. Such systems would also be advantageous to the healthcare fraternity.

2. Many studies have extensively evaluated FER models using benchmark datasets including CK+, JAFFE, KDEF, and FER2013. However, we have identified some significant limitations. Though classic, both CK+ and JAFFE encompass the strict lab-controlled environment. Hence they have restrictions in generalizing to real-world applications. Further, both datasets are devoid of occlusions and have a limited sample size of 981 and 220 respectively. Therefore, we conclude that these datasets are not sufficiently large or diverse to satisfactorily address the robustness of FER models.

3. Moreover, several works have addressed the predominant use of specific DA techniques. There is need for research that explores the impact of various categories of DA on system performance.

1.2 Research gaps

1. Large, robust datasets combining lab-controlled and in-the-wild data is essential for enhancing accuracy and ensuring real-world applicability of FER. Currently, there is lack of such data.

2. Further, there is lack of research on comprehensive frameworks that combine data merging and heterogeneous augmentations.

3. Also, examining the impact of negative emotions on long-term user behavior is still unexplored. Hence, there is critical need for a holistic system with focus on negative affect detection and tailored behavioral support.

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4. Additionally, there is scarcity of studies that showcase the outcomes of combining data merging with diverse augmentation strategies within a deep learning framework.

5. Also, there is lack of innovative augmentation techniques in this field.

1.3 Objectives

1. To propose a comprehensive framework for a negative affect detection system.

2. To introduce a novel multi-stage data augmentation and merging framework for the systematic combination of augmentation and merging processes.

3. To examine the impact of stages in the framework on the performance of the system.

4. To incorporate both geometric and advanced DA in proposed framework and evaluate the impact of DA on system performance.

5. To create and validate the custom dataset w.r.t. its usefulness in emotion recognition.

6. To propose a custom deep model for emotion recognition.

7. To determine the efficacy of the proposed model by validating it with popular FER datasets, while also benchmarking it with existing deep architectures.

1.4 Novelty

1. This paper introduces a comprehensive framework for negative affect detection. It encompasses an innovative recommendations engine that provides timely and personalized, behavioral-support recommendations. This feedback-based approach promotes the development of a holistic system that benefits the key stakeholders, including the affected individuals, researchers, medical practitioners, and the healthcare fraternity.

2. An interesting and extensive three-stage framework for combining Data Augmentation and Merging is introduced in this paper. This framework creates a domain-bias free dataset, created with the methodical integration of augmentation and merging of heterogeneous samples from varied benchmark datasets.

3. Further, an interesting concept of Augmentation-Based data Fragments (ABFs) is introduced. ABFs segment the image samples acquired from different augmentations. This concept contributes to the heterogeneity and generalization of samples in the custom generated data.

1.5 Contributions of current work

1. The chief contribution of this paper is introducing RBF-NA, a Recommendations and Behavioral Support based Framework for Negative Affect detection. RBF-NA is a holistic, multimodal framework for mental health monitoring. Powered by deep learning, RBF-NA targets the detection of negative emotions. With its two-level stratification strategy, RBF-NA predicts the at-risk candidates classifying them into low-risk and high-risk. For any fluctuations in emotional states, the low-risk candidates shall be monitored for an extended time; while the high-risk candidates will immediately be addressed by the alert

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

mechanism. A systematic feedback mechanism will facilitate timely notification to the concerned healthcare fraternity while also providing personalized behavioral-support recommendations including suggestions for therapies, forums, and treatment.

2. Due to the complexity of RBF-NA, this paper focuses on the Data Augmentation and Merging framework and its deployment in face emotion recognition system as a proof of concept. Thus, another interesting contribution of this paper is introducing the Hybrid-Multi Stage Augmentation and Merging (H-MSAM) framework. H-MSAM is an innovative and extensive framework for combining the augmentation and merging of heterogeneous data acquired from numerous benchmark datasets. It addresses the following issues commonly faced by classic datasets in the field: class imbalance, small sample size, generalization, and domain bias.
3. Additionally, the current work presents a large custom dataset that is free from domain barriers.
4. Additionally, C-FED, a custom CNN model is proposed for efficient facial emotion detection. Promising results are achieved with C-FED.
5. Extensive experiments are designed to validate C-FED on three benchmark datasets. C-FED achieved excellent performance with highest accuracies of 99.75% and 85.87% on CK+ and KDEF respectively. C-FED surpasses the existing works in literature. Further, C-FED was validated with competitive architectures, such as ResNet and VGG16. C-FED outperformed both ResNet and VGG16, achieving an accuracy improvement of 6.87% and 5.13%, respectively. These encouraging results suggest its potential for real-world applications.

The organization of this paper is as follows. Section 2 presents Related works, Section 3 covers Methodology and details about datasets used. Sections 4 and 5 present the extensive Experimental work and Results respectively. Section 6 mentions the Limitations of current work. Section 7 elaborates the Discussion, while Section 8 articulates the Conclusion and future work.

2. Related works

2.1. Data Augmentation and FER systems

Data Augmentations (DA) are the set of techniques designed to expand and improve the size and quality of training data [6],[7]. DA methods treat overfitting by addressing the primary cause of the problem and resolve the issues prevalent in the training dataset. DA relies on the assumption that additional information can be derived from the original data by using different augmentations [8]. DA employs basic techniques such as Data warping and Oversampling. Data warping modifies images while preserving their labels, utilizing the techniques like geometric/color transformations, adversarial training random erasing, and neural style transfer. Oversampling generates synthetic instances for the training set through methods such as image mixing, feature space augmentations, and generative adversarial networks [9],[10].

Highlights of FER systems employing DA are summarized herein.

Received: August 09, 2025

International Journal of Applied Mathematics
Volume 38 No. 5s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The use of extensive datasets is typically essential to mitigate overfitting. [11] underscores that several studies have extensively evaluated FER models using public benchmark datasets including CK+, JAFFE, KDEF, and FER2013. However it is observed that these data suffer from limitations of sample size and diversity. [11] highlights a crucial observation that the performance of FER models frequently fluctuates across different datasets owing to discrepancies in the representation and labeling of emotions. [12] implements DA to overcome the issue of small sample size. However, it is observed that the augmented dataset still lacks in-the-wild expressions, thereby delimiting its real-world applicability. With the effective generation of facial images using Stable Diffusion, it is observed that only a small quantity of synthetic data is sufficient for training. However, some limitations are noted. The AI created synthetic images lack inherent human traits, and the diminished effectiveness of system in cross-dataset scenarios suggests the impracticality of entirely substituting real facial images with synthetic ones. Moreover, data merging is only performed on in-the-wild datasets and no benchmarking is performed with existing methods.

A vision transformer that exploits local spatial relationships is presented in [13]. Although high performance is achieved on benchmark datasets, future research is to prioritize augmentation techniques and enhance generalization of models. An interesting approach of applying attention to the face as well as specific zones is presented in [14]. A key future direction is to experiment with data from diverse domains and assess generalization. Though innovative, the cross-dataset methodology [15] requires performance enhancement. [16] proposes a methodology for combining multiple datasets and evaluates the CNN-based model using both single and cross-dataset approaches. Cross-dataset approach marks an improved accuracy of 73.05% in comparison to 61.78% accuracy with single-dataset approaches. Despite the extensive experimentations a significant limitation observed is the exclusion of FER+ dataset citing challenges associated with incorporating in-the-wild data. Further, [17] emphasizes the role of deep architectures for DA in FER.

Despite numerous contributions some works report lower performance thereby highlighting the need for improvements in future research. [18] presents an unsupervised cross-domain FER utilizing Adversarial Learning for blurring the feature representations. Recognition on CK+ was only 88.71%. [19] introduces the integration of Edge Computing to address the limitations of Cloud Computing. While time benefits are apparent, the accuracy on CK+ is 93.85% despite the fact that the dataset consisted of strictly lab-controlled samples.

Research gaps of some interesting works in this field are presented here. It is observed from [20] that the class imbalance in FER severely impacts generalization. The future work includes refining the process of utilizing synthetic data, perform thorough analysis of its impact on performance, explore various strategies to augment data, and propose methods for combining DA and synthetic data on FER. Future work of [21],[22] includes investigation of additional sophisticated augmentation techniques followed by experimentation on larger, diverse data. [23] aims to explore the various rates of class-wise augmentation to be applied to data-scarce scenarios. A hybrid augmentation method is proposed in [24] and improved

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

performance is achieved on four public datasets. However, it is noted that only accuracy is considered while measuring the performance, also, the results do not demonstrate generalization. [25] suggests lack of innovative augmentation techniques while emphasizing the need for novel, complex strategies and their integration with deep models. It is noted that there is no agreement on the optimal percentage to yield the best performance, however augmentations over 55% are not recommended [26].

2.2. Emotion-aware Recommendation systems

[27] examines an interesting research of the cutting-edge use of wearables and deep learning to improve emotional health and stress management for persons with negative affect. It examines the individualized methods for enhancing emotional well-being, using them to customize interventions that meet unique needs and reactions. An interesting application of emotion recognition is to detect the emotional reactions that substantially deviate from expected patterns in specific situations or individuals. This involves recognizing the sudden changes of emotion, differences between various emotional cues, or persistent, uncharacteristic patterns of emotion. The importance of identifying such anomalous emotions has grown considerably, particularly in the systems designed for monitoring mental health. In such systems, early discovery can enable more context-sensitive interventions [28]. Hence, systems that target early detection of negative affect is crucial.

There is a growing need for research on wellbeing/behavioral support-based recommendations [29],[30]. [31] presents a robust, theory-driven framework of user characteristics to facilitate the comprehensive customization of digital wellness interventions. This model suggests the objectives for behavior change and activities across different lifestyle domains. Although the prototype demonstrates a reduction in the perceived effort of coaches in selecting suitable tasks, it did not alleviate the challenge of identifying behavior change objectives. The interesting study [32] investigates the viability of providing personalized recommendations for health-promoting activities to users by analyzing data collected from a clinical sample with mood disorders and baseline. Activities were modeled as bag-of-words to predict the outcomes of mood. While the study successfully demonstrated feasibility in recommending specific activities, it is observed that the analysis was simulated and offline, with future research focusing on developing a context-aware model.

[33] presents models that emphasize the role of negative emotions (frustration, sadness, and anger). It concludes that the presence of noisy and ambiguous data negatively impacts the accuracy of system. However, the paper does not sufficiently explore the effects of prolonged negative emotional states on recommendations. [34] presents a hybrid, collaborative filtering approach that integrates negative emotions such as dissatisfaction. However, it is observed that the model's dependence on emotional cues renders it overly sensitive to transient negative emotions. To enhance the contextual relevance in recommendations, [35] introduces a deep model that considers negative affective states, including frustration and stress.

International Journal of Applied Mathematics
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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3. Methodology

3.1. Proposed architecture

RBF-NA is a comprehensive multimodal framework. The proposed architecture of RBF-NA is illustrated in Figure 1.

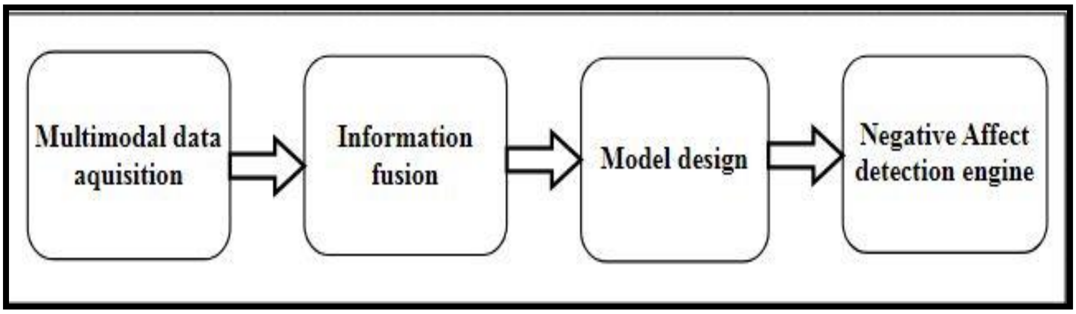

Figure 1. Proposed architecture of RBF-NA

RBF-NA consists of four distinct modules which are described as follows.

1. Data Acquisition module: This module collects multimodal data including facial images, questionnaire responses, and gestures.

2. Multimodal Information Fusion module: This module introduces a method for multimodal data fusion, designed to operate at both low-level, high-level features. The objective is to extract semantically rich information from the acquired data.

3. Model Design module: This module addresses critical aspects of model development, including architecture design, creation of emotion representations, model training and testing, performance evaluation, and optimization.

4. Negative Affect Detection and Recommendation module: The final module focuses on identifying negative affect and delivering personalized recommendations to the affected individuals. RBF-NA predicts the at-risk candidates and classifies them into low-risk and high-risk with its two-level stratification strategy. RBF-NA proposes the acquisition of three modalities – facial image, responses to questionnaires (both objective and subjective), and gestures. Each modality is computed by a dedicated unit named as Facial Expressions Recognition unit, Questionnaires unit, and Gestures unit respectively. This multimodal design shall fortify the semantic data and strongly contribute in developing a robust system. The Questionnaires unit shall employ two questionnaires for robust, quantitative assessment of strong negative affect. These are, Mood and Anxiety Symptoms Questionnaire (MASQ) [36] and Aphasic Depression Rating Scale (ADRS) [37]. Considering the complexity of proposed system, as a proof of concept this paper presents experimental results utilizing the face modality. The Facial Expressions Recognition module is described further.

Figure 2 shows workflow of the Facial Expressions Recognition module.

As observed in Figure 2, FER comprises of four significant units. The first unit encompasses

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

an elaborate survey of all existing, relevant face expression recognition-related datasets followed by identifying the most suitable datasets aligned with current research objectives. The second unit performs Data Pre-processing by handling noise removal, face detection, alignment, normalization using Haar cascade. The third unit is the most significant contribution of current work. It presents the H-MSAM framework. This framework introduces multi-stage augmentations and merging of diverse data, leading to the generation of custom, balanced, domain-bias free data. This data has a larger sample size as compared to the independent FER datasets. The fourth unit focuses on Emotion Recognition. The latter comprises a custom deep model that detects emotions from the human face. Architectural details of the model are presented in ensuing section.

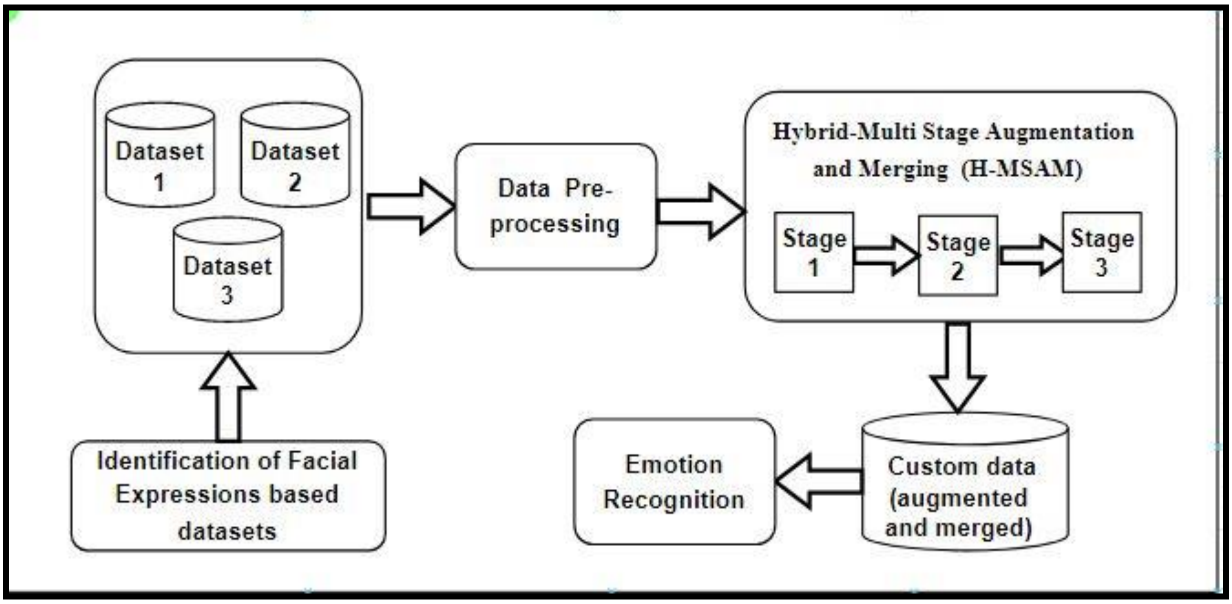

Figure 2. Micro design of Facial Expressions Recognition module

3.2. Datasets used

1. Extended Cohn-Kanade (CK+) [38]:

CK+ includes sequences that feature 123 subjects aged 18-30 years. These images were obtained under the controlled conditions in a laboratory setting. It encompasses six primary classes anger, sadness, fear, disgust, surprise, and happiness. CK+ is widely employed in Emotion Recognition research and benchmarking, since it exhibits significant diversity across each expression category thereby becoming a preferred choice for training and evaluating algorithms.

2. FER2013 [39]:

FER2013 is segmented into three parts, a training subset comprising 28709 images, a validation and test subset each with 3589 images. FER2013 represents seven emotions, anger, disgust, neutral, fear, sadness, happiness, and surprise. Due to its standardization FER2013 is popularly used for benchmarking.

International Journal of Applied Mathematics
Volume 38 No. 5s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3. KDEF [40]:

KDEF comprises of 4900 images representing seven distinct emotions. These images feature various profile views of individuals including frontal, whole right, whole left, half of right, half of left and angles. KDEF poses challenges due to the partial visibility of one eye and one ear in the full right and full left views thereby adding complexity to emotion recognition. KDEF is designed to be diverse in terms of age and gender. This diversity helps ensure it is widely representative.

3.3 Proposed Hybrid-Multi Stage Augmentation and Merging (H-MSAM) framework

Macro design of proposed H-MSAM framework is presented in Figure 3.

Dataset 1 comprising of lab-controlled samples (D-L1) and Dataset 2 comprising lab-controlled samples (D-L2) are the input to Stage 1.These datasets are augmented with the following geometric augmentation techniques: horizontal reflection (h), translation (t) and cropping (c). In Horizontal reflection the image is mirrored across a line to produce a reversed image. In Translation each point of the shape shifts by the same distance and in the same direction maintaining its shape, size, and orientation; while Cropping trims parts of an image highlighting a chosen area. These techniques are applied inline with the proposed Augmentation-Level 1 (AG-L1) algorithm.

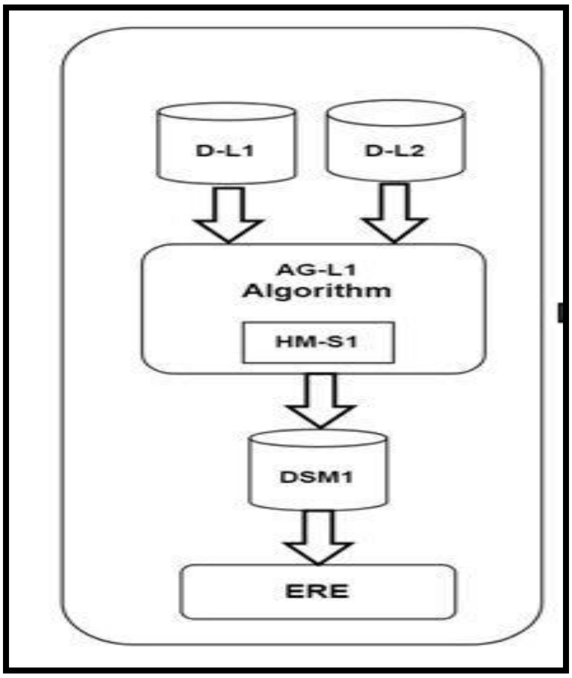

Figure 3. Macro design of proposed H-MSAM framework

AG-L1 algorithm is presented as under.

Start

For each Dataset d

i. Compute h(d) // where h=horizontal reflection

Received: August 09, 2025

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ii. Compute t(d) //where t = translation

iii. Compute c(d) // where c =crop

iv. Vector *O*=(h(d) U t(d) U c(d)) // merging all augmented samples

// t= number of labels

v. Vector *S*= randomly select n samples from *O* //data sampling

vi. TR={s ε | select the samples such that |TR|= 0.8 * *S*} // creating train set

// from the remaining samples in S, create the Test set by sampling 20% data

vii. TS={s ε | select the samples such that |TS|= 0.2 * *S*} // creating test set

viii. Perfo-Check ()

ix. HM-S1(d)

End

Perfo-Check (TR, TS) // Performance Evaluation

i. Train the C-FED model on TR

ii. Test the performance on TS.

iii. Fine tune the model.

iv. Perform k-fold cross validation on {TR,TS}

v. Evaluate the performance of C-FED using accuracy, precision, recall, F1-score.

vi. Save the results.

End

HM-S1(D) // Heterogeneous Merging at Stage 1

For i=1 to d // where d = number of datasets

For j=1 to e // where j=number of emotion class labels

Vector L = U(*O*) //stratified merging of all augmented samples

End

DSM= U(*L*) //resultant Dataset

End

Stop

As observed from AG-L1Algorithm, D-L1 and D-L2 are the two significant inputs to AG-L1. Stage 1 deals with two lab-controlled datasets. Thus, CK+ (representative of D-L1) and KDEF (representative of D-L2) are identified as inputs. Being the initial step in the framework, Stage 1 is exclusively designed to deal with geometric transformations. Thus, the techniques of horizontal reflection (h), translation (t) and cropping(c) are applied on both the

Received: August 09, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

datasets. This is followed by merging the augmented samples in the vector O by performing random sampling without replacement. Further, the Train and Test sets are created from the multi-labeled data from O using 80:20 principle. The Perfo-Check function evaluates performance of the proposed C-FED model on aforementioned augmented data which is generated by implementing AG-L1 using the measures of accuracy, recall, F1-score, and precision. This is followed by invoking the function Heterogeneous Merging at Stage 1(HM-S1). The latter performs an emotion-wise stratified union of the custom-generated data. This data acquired from Augmentation and HM-S1 is referred as DSM1 (Dataset resulting from Stage 1 Augmentation and HM-S1). This step is followed by invoking the Emotion Recognition Engine (ERE) module which is elaborated in the ensuing section.

3.4 Proposed Emotion Recognition Engine (ERE) module

A custom CNN model for emotion recognition is proposed in this module, and is hereafter addressed as Convolutional-Face Emotion Detection (C-FED). The images sized 48 x 48 are fed as input initially to the first convolution layer. There are two convolution layers and blocks of Batch Normalization, Activation, Max Pooling, and Dropout. The purpose of these blocks is to extract maximum features. The first block is followed by the third convolution layer. Batch Normalization is added to normalize the input of intermediate layers. Max pooling with size 2 x2 is employed with two strides for dimensionality reduction. Rectified Linear Unit performs activation. All filters in convolutional layers are 3x3 with stride of 1 each. Two fully connected layers are employed after flattening of output from the third pair of convolutional layer. Output of last fully connected layer is fed to softmax for classification of image into either of the seven class labels of angry, fear, disgust, sad, happy, neutral, or surprise. Table 1 presents the values of parameters used in fine tuning of C-FED.

Table 1. Hyper parameter tuning.

Parameter	Value
Batch size	32
Learning rate	0.0001
Optimizer	Adam
Epochs	25
Loss Function	Categorical cross entropy

4. Experimentation

As CK+ originally had fewer samples (i.e. 504) augmentation generated 253 additional samples based on the augmentation ratio. KDEF did not have any skewed data, augmentation generated 980 samples. FER2013 had 35,594 original samples and augmentation generated an additional 16,797 samples. In-depth details of augmentations in the various stages of H-MSAM is presented in Table 2.

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Volume 38 No. 5s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Table 2 presents details of the augmentation types and number of samples acquired per augmentation, in each of the three stages in H-MSAM. Stage 1 introduces the three geometric augmentations of horizontal reflection (h), translation (t) and cropping (c) on the two lab controlled classic datasets, KDEF and CK+. A total of 1,233 augmented samples are acquired in Stage 1 and stored in the resultant dataset DSM1. In Stage 2, DSM1 and the spontaneous dataset (FER2013) are considered as input to system. Advanced augmentations (l, n, and b) are performed along with the three geometric augmentations. An important characteristic of Stage 2 is introduction of the ABFs. Stage 2 yields 73,349 samples in the resultant dataset DSM2. Stage 3 does not include the heterogeneous merging step, but performs the three geometric and advanced augmentations each on DSM2 to yield a whopping 2,93,376 samples in the final resultant dataset DS1.

Table 2. Details of augmentations in various stages of H-MSAM

H-MSAM stage	**Augmentation type**	**Name of dataset**		**Total samples**
Stage 1	Geometric	Lab controlled dataset 1 (CK+)	Lab controlled dataset 2 (KDEF)	
	h	84	326	1233
	t	84	327	
	c	85	327	
Stage 2	**Augmentation type**	**Name of dataset**		**Total samples**
	Geometric + Advanced	DSM1	Spontaneous dataset (FER2013)	
	l	205	2799	73349
	n	206	2800	
	b	205	2800	
	h	205	2799	
	t	205	2800	
	c	206	2800	
	HT	410	5599	
	TC	411	5600	
	HC	411	5599	
	HTC	1232	8399	

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

	LN	410	5599	
	NB	411	5599	
	LB	411	5598	
	LNB	1232	8398	
Stage 3	**Augmentation type**	**Name of dataset**		**Total samples**
		DSM2	--	**293376**
	l	12224	--	
	n	12224	--	
	b	12225	--	
	h	12224	--	
	t	12224	--	
	c	12224	--	
	HT	24448	--	
	TC	24448	--	
	HC	24448	--	
	HTC	73344	--	
	LN	24448	--	
	NB	24448	--	
	LB	24448	--	
	LNB	73344	--	

5. Result Analysis

All experiments were conducted on a system featuring an Intel Core i9-7980XE processor, 64 GB RAM, and two NVIDIA GeForce GTX 1080 Ti GPUs, each equipped with 11 GB of dedicated video memory. This robust configuration ensured efficient handling of computationally intensive tasks and large-scale data processing.

5.1 Impact of H-MSAM stages on performance of the system

Thorough experimentation was performed to evaluate the impact of various H-MSAM stages on the overall performance of system using measures of precision, accuracy, F1, recall.

Let x=true positive, y= false positive, z=true negative, w= false negative

$$precision = x / (x + y) \qquad ---(1)$$

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

recall = x / (x + w) --- (2)

F1= (2 * precision * recall) / (precision + recall)--- (3)

accuracy=(x + z)/(x+y+w +z) --- (4)

specificity = z / (z + y) ---(5)

sensitivity = x / (x + w) --- (6)

Results achieved at each stage is presented in Figure 5.

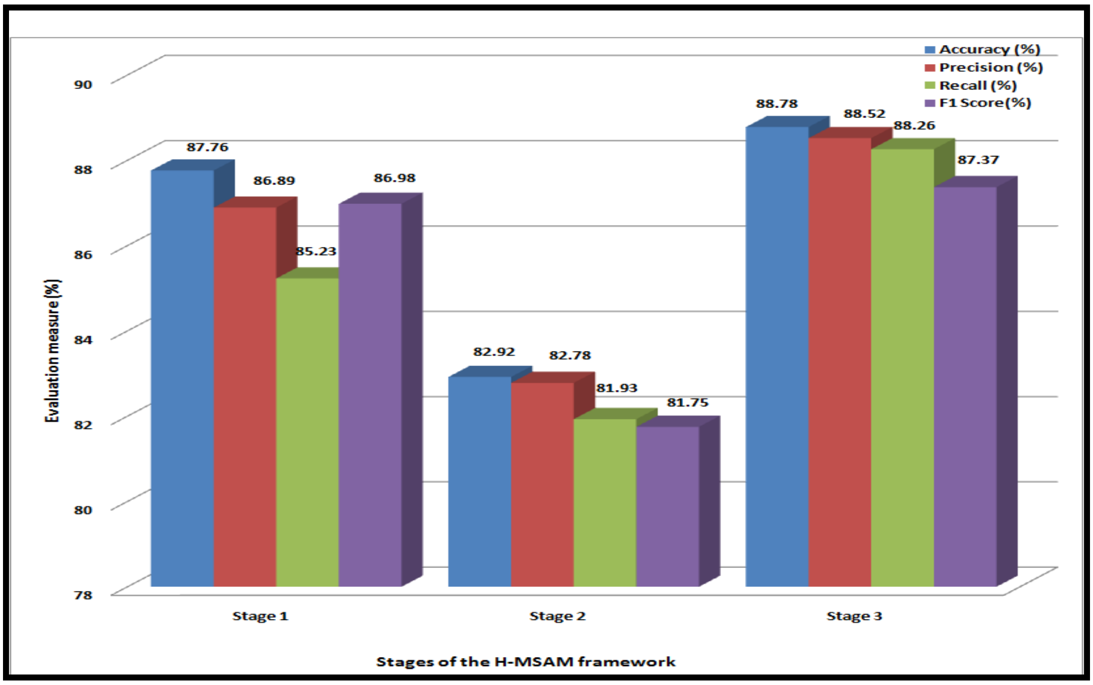

Figure 4. Performance comparison of H-MSAM stages

Figure 4 presents the performance analysis across stages 1 to 3. It is measured using accuracy, precision, recall, and F1 score. It is observed that despite the increased heterogeneity, Stage 3 outperforms the preceding stages with increased performance. This demonstrates efficacy of H-MSAM. It is worthwhile to evaluate the three stages wrt the generalization gap achieved at every stage.

Figure 5 shows confusion matrices. H-MSAM Stage 1 achieves excellent accuracy despite the merging of two datasets. Each emotion label achieves a high accuracy of over 80%, with the highest accuracies of 88% and 90% achieved on sad and angry emotion labels respectively. Despite the excellent results some observations are noted. Although the neutral label achieved good accuracy of 85%, it is misclassified as happy, angry, and fear in 4%, 4%, and 5% of instances respectively. Results obtained at Stage 2 are also encouraging despite the fact that heterogeneity was introduced the most during this stage. Each emotion label achieves a good accuracy of over 75%. Inline with Stage 1, Stage 2 also demonstrates good performance in detecting the negative emotions. Stage 3 yields excellent performance with all emotions achieving high accuracy of over 85.79%. The highest performance of 92% was achieved on the sad emotion.

Received: August 09, 2025

International Journal of Applied Mathematics
Volume 38 No. 5s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

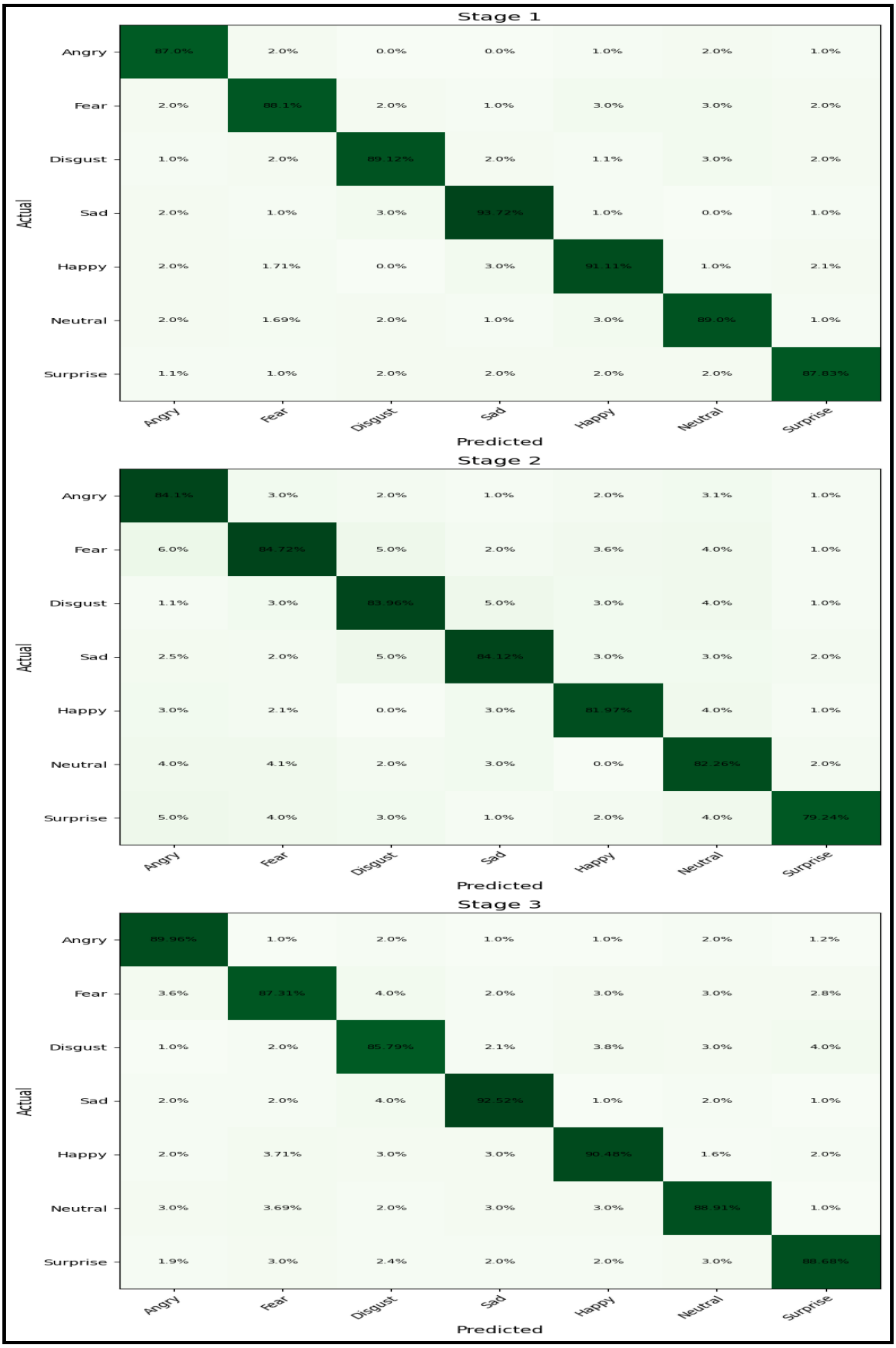

Figure 5. Confusion matrix on each stage of H-MSAM framework

International Journal of Applied Mathematics
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5.1.1 Evaluating the granular performance of system

To examine the performance of system at the micro level, authors conducted granular performance of the system at the ABF level. These results are depicted in Figure 6.

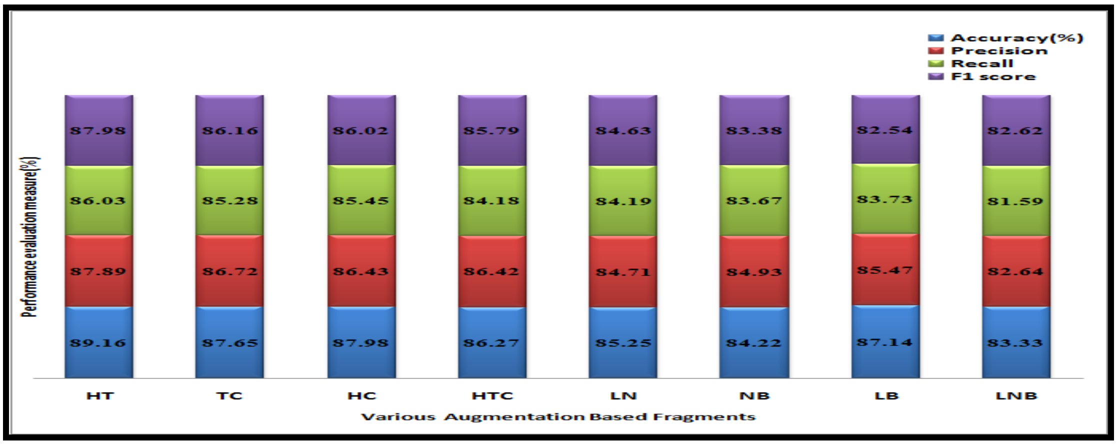

Figure 6. Granular ABF-wise performance of system

Figure 6 shows the performance analysis measured by accuracy, precision, recall, and F1 score for each ABF i.e. HT, TC, HC, HTC, LN, NB, LB, and LNB. All ABFs achieve an excellent accuracy of over 83%. It is observed that HT achieved the highest accuracy of 89.16% as compared to other ABFs. HT and TC achieve the highest F1 scores of 87.98% and 86.16% respectively, thereby demonstrating generalization capability of H-MSAM.

5.2.1 Performance analysis of negative emotions

It is observed from Figure 7 that all the four negative emotion labels angry, fear, disgust, and sad achieved high precision of 88.89%, 87.34%, 89.41%, and 89.56% respectively. Further, it is noted that the sad emotion label achieved a high accuracy of 92.52% followed by angry emotion achieving an accuracy of 89.96%. These results suggest the capability of H-MSAM in detecting negative emotions. Figures 7 and 8 demonstrate the excellent performance of C–FED. The sad emotion achieves highest performance with 95.24% on CK+ and 92.52% on custom data. Similar observation is noted for F1 score. The sad emotion achieves the highest F1 score of 92.52% and 96.34% on custom data and CK+ respectively. These results suggest the efficacy of H-MSAM in detecting negative affect.

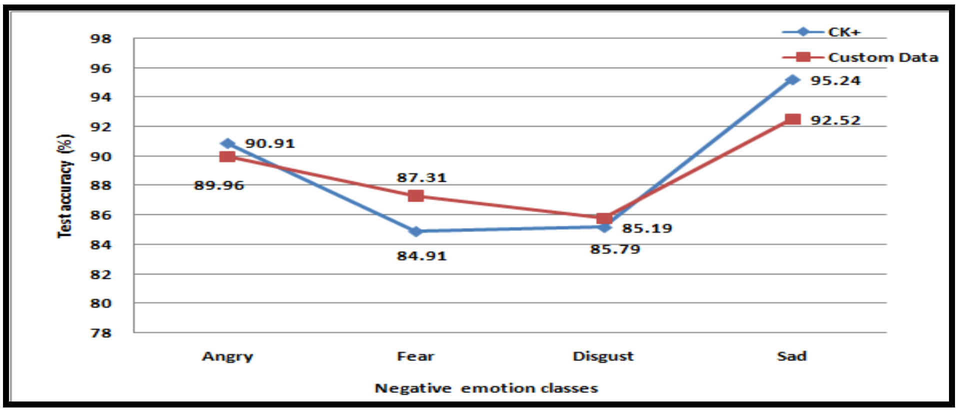

Figure 7. Comparative analysis of accuracy of CK+ vs Custom data

Received: August 09, 2025

International Journal of Applied Mathematics
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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

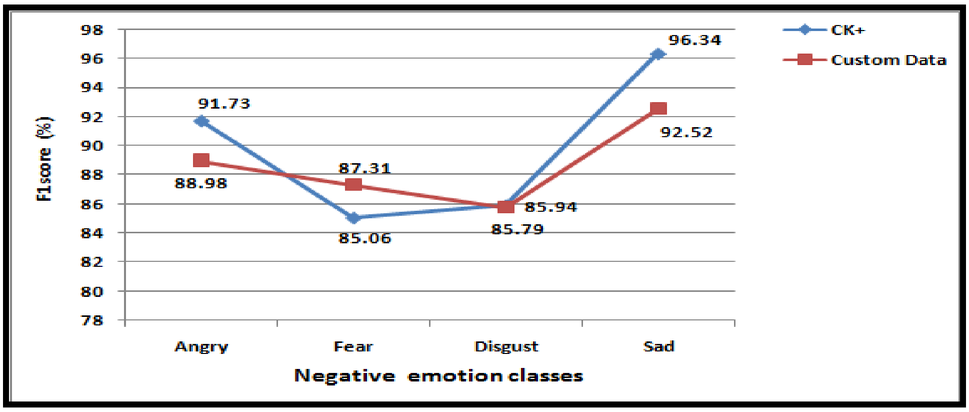

Figure 8. Comparative analysis of F1 score of CK+ vs Custom data

5.3 Performance evaluation of the baseline C-FED model

Comprehensive experiments were performed to assess the performance of C-FED on all three benchmark datasets. The results achieved are presented in Figure 9.

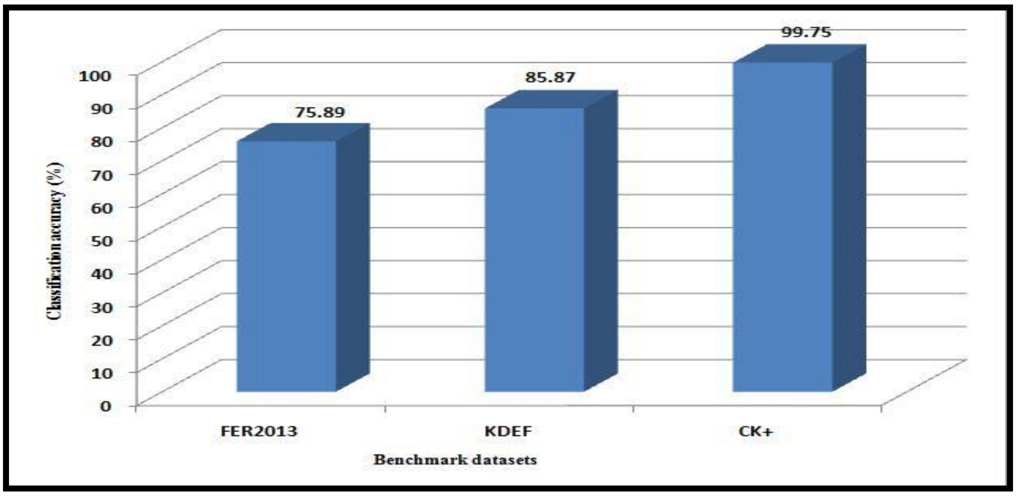

Figure 9. Performance of C-FED on benchmark data

CK+ outperforms KDEF and FER2013 with an excellent performance of 99.75% classification accuracy.

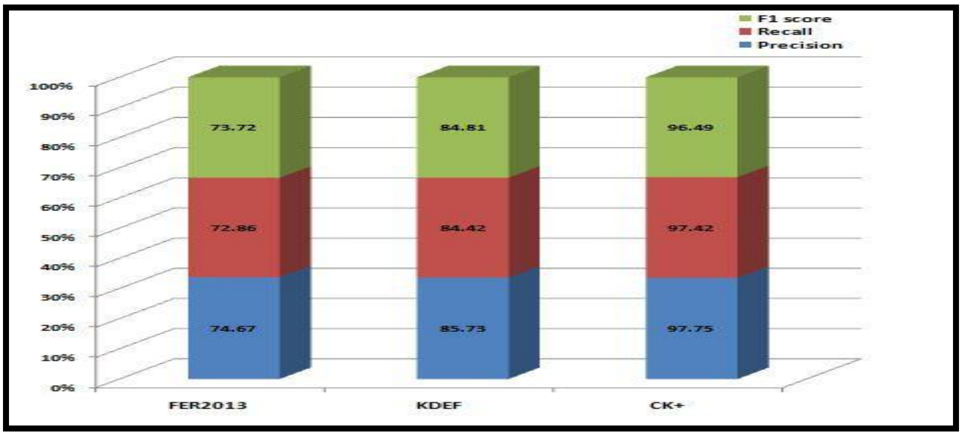

Figure 10. Performance analysis on benchmark data

Received: August 09, 2025

International Journal of Applied Mathematics
Volume 38 No. 5s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Figure 10 shows the detailed performance analysis of C-FED on FER2013, KDEF and CK+. Analysis was performed using precision, recall, and F1 score. CK+ outperforms FER2013 and KDEF with an excellent precision, recall, and F1 score of 97.75%.

Figure 11 depicts the confusion matrices demonstrating the performance of C-FED on all three benchmark datasets.

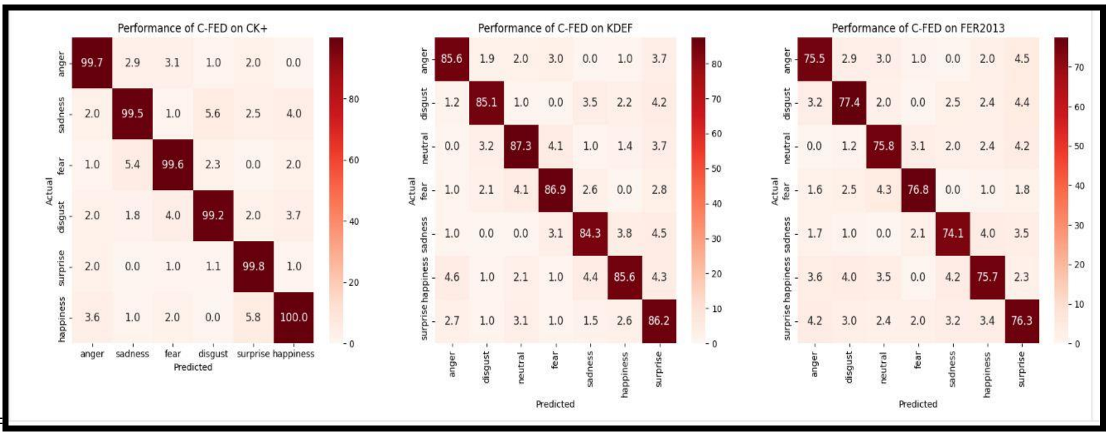

Figure 11. Confusion matrix representing results of C-FED on three benchmark data

C-FED achieves a remarkable accuracy of 99.75% on CK+. Further, excellent performance is achieved on every emotion label, with sad and angry labels achieving the highest accuracies of 95.24% and 90.91% respectively. The misclassifications are nominal. C-FED also achieves good results on FER2013 and KDEF. The best performance on FER2013 was achieved on the emotion labels disgust and fear with accuracies of 77.4% and 76.8% respectively.

5.4 Comparative analysis of C-FED with competitive architectures

The performance of C-FED is further validated by benchmarking it with VGG16 and ResNet architectures. Results of implementing VGG16, ResNet, and C-FED on CK+, KDEF, and FER2013 datasets respectively is depicted in Figures 12 to 13. This detailed comparative analysis is performed using recall, precision, and F1 score.

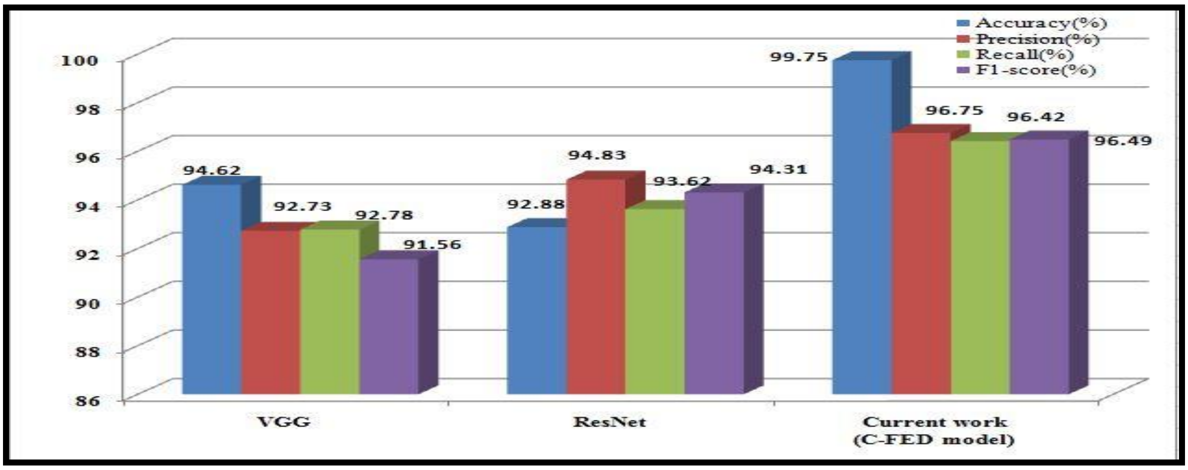

Figure 12. Comparative analysis of competitive architectures on CK+

Received: August 09, 2025

International Journal of Applied Mathematics
Volume 38 No. 5s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

C-FED achieves excellent results on CK+. It is observed that C-FED outperforms VGG and Resnet architectures with an excellent precision, recall, and F1 of 96.75%, 96.42%, and 96.49% respectively.

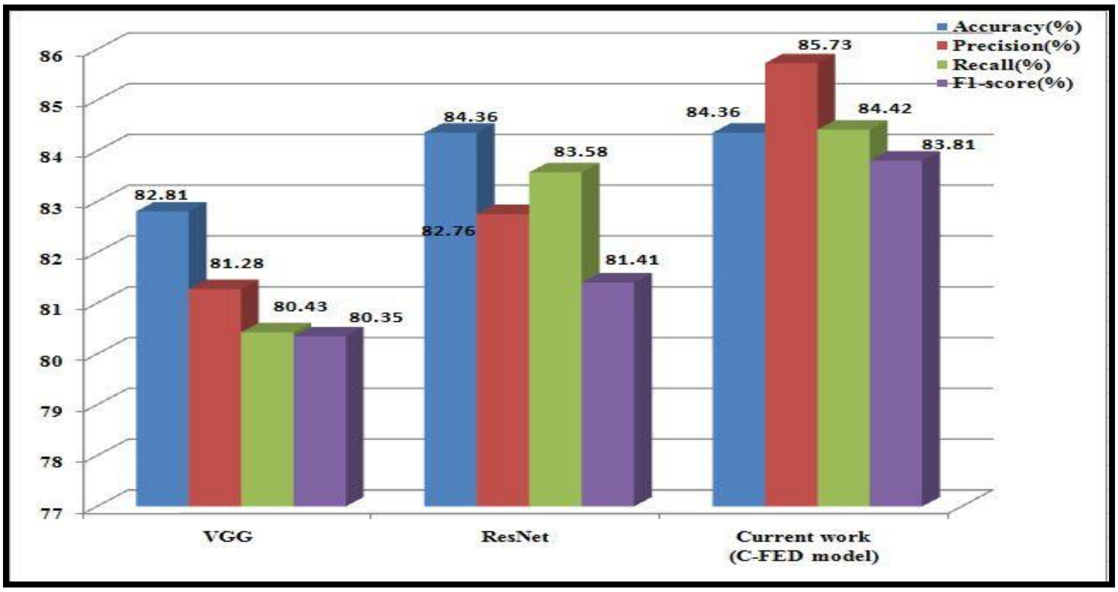

Figure 13. Comparative analysis of competitive architectures on KDEF

C-FED achieves excellent results on KDEF. It is observed that C-FED outperforms VGG and Resnet architectures with an excellent performance of 85.73% precision, 84.42% recall, and 83.81% F1 respectively.

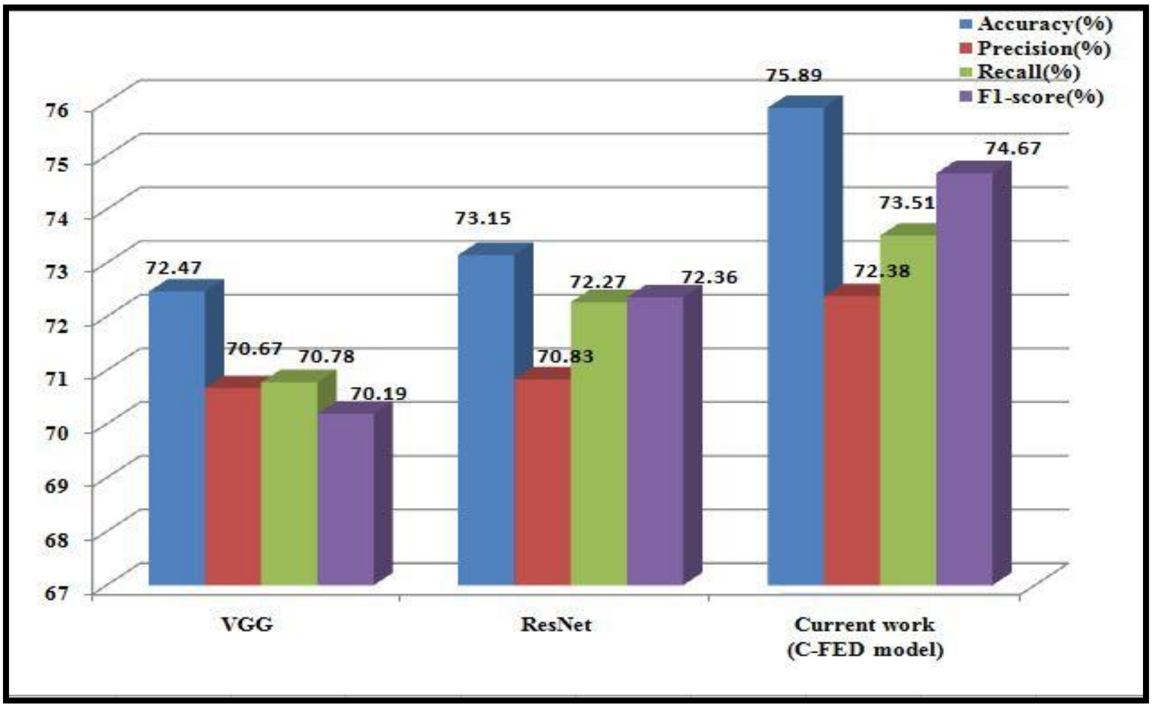

Figure 14. Comparative analysis of competitive architectures vs. C-FED on FER2013

C-FED achieves good results on FER2013. C-FED outperforms VGG and Resnet architectures with a good performance of 72.38% precision, 73.51% recall, and 74.67% F1

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

respectively.

5.5 Comparative analysis with State-of-the-Art (SOTA)

Comparative analysis of current work with the relevant, existing works in literature is tabulated in Table 3.

Table 3. Comparative analysis of current work with SOTA

Method	Classification accuracy (%)
VGG-face network[41]	77.5
MixAugmentation+Flip [42]	87.4
RAN [43]	86.90
Ad-Corre [44]	86.96
mSVM+DLP CNN [45]	74.20
Face Behaviour net [46]	78
PRATIT [47]	78.52
Proposed work (C-FED)	**88.78**

6. Discussion

Baseline C-FED outperforms existing works with an excellent accuracy of 99.75% on CK+, 85.87% on KDEF, and 75.89% on FER2013 respectively. The comparative analysis presented in Table 3 depicts the enhanced performance of C-FED in comparison to relevant works in literature. It is worth comparing current work with significant existing works on data merging and augmentation based frameworks for emotion recognition. In contrast to [19], the custom data generated in current work is balanced, diverse, and domain-bias free. C-FED model outperforms [48] with an improvement of 1.35% and 10.89% respectively in the classification accuracy on CK+ and FER2013. Further, current work outperforms [49] by presenting the balanced data that is rich in heterogeneity, and is further successfully validated with C-FED. Additionally, current work outperforms [16] with an increased accuracy of 8.78%, along with higher generalization. [50] achieved test accuracies of 63.39%, 64.59% on the original, augmented FER2013 respectively. Current work surpasses [50] with an increase of 12.5% in accuracy thereby highlighting the competitiveness of H-MSAM.

Effective DA techniques play a crucial role in the various applications of FER, including- anxiety detection [51],[52], personality prediction [53],[54], healthcare [55], sentiment analysis [56].

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8. Conclusion and Future work

This paper presents RBF-NA, an innovative and multimodal framework for detecting negative affect. Further, this paper introduces an innovative and extensive pipeline, Hybrid-Multi Stage Augmentation and Merging (H-MSAM). H-MSAM is designed to combine the augmentation and merging of heterogeneous data across a well-designed multi-stage framework. H-MSAM successfully addresses the existing challenges of class imbalance, small sample size, generalization, and domain bias. With the semantically rich combination of geometric and advanced augmentations, H-MSAM demonstrates marked improvement in classification accuracy by 13.31% on CK+, 16.96% on KDEF, and 19.44% on FER2013 over the baseline. C-FED achieves excellent accuracies of 99.75% and 85.87% on CK+ and KDEF respectively. Comparative analysis with other deep architectures also yields promising results, with C-FED demonstrating better performance over ResNet and VGG16 with an increased accuracy of 6.87% and 5.13% respectively. Also, the excellent performance achieved using F1 scores, suggesting the generalization ability of C-FED. Current work surpasses the related works that proposed frameworks for data merging/augmentations.

A significant direction for future research involves integrating advanced techniques such as adversarial training, color space transformation. The current framework will be extended in future to include the additional benchmark data. The contributions presented in this research are poised to significantly advance the existing body of knowledge in FER. Moreover, the enhanced H-MSAM framework holds considerable potential for improving the effectiveness of mental health monitoring systems with the timely and efficient detection of negative emotions, thereby offering substantial benefits to both the scientific and healthcare communities.

S. S. Panicker author took responsibility of conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, writing original draft. P. Gayathri carried out supervision, review & editing, project administration, resources.

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