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Artificial Intelligence-Based Facial Expression Recognition for Identifying Customer satisfaction on Products

Samreen Ihsan*, Ihsan Adil, Anwar Zeb, Sajad Ulhaq, Umer Ahmad, Irshad Ali Khan and Muhammad Khalid

***Abstract* – Facial Expression Recognition (FER) for Identifying Customer Satisfaction on Products is one of the most powerful and challenging research tasks in social communication. Artificial intelligence (AI)-based emotion recognition harnesses the collective strength of machine learning, deep learning, and computer vision to decipher the subtleties of human emotions. By intricately analyzing facial expression, including the nuanced movements of the mouth, eyes, and eyebrows. Recent innovations have driven notable progress in face detection and recognition that enhance performance and reliability. This study focuses on leveraging AI-based facial expression recognition to identify customer satisfaction with products. The objective of this research is to develop a robust and accurate facial expression recognition system capable of analyzing customer emotions and determining their satisfaction levels based on their facial expressions. The proposed study used a hybrid convolutional neural network (CNN) and deep neural networks (DNN) model to extract meaningful features from facial images and classify them into different emotional states. The trained model is to be evaluated using a separate test dataset to measure its performance in accurately recognizing customer emotions and assessing satisfaction levels. The evaluation metrics include accuracy, precision, recall, and F1-score. The proposed experiment achieved excellent result with a real-time image-based dataset.**

Keywords— Artificiall Intelligence, Facial Expressions Recognition, Customer Satisfaction, Deep Learning, Machine Learning, Real-Time analysis, Emotions Detection.

I. INTRODUCTION

Emotions are crucial to the human experience, impacting decision-making, behavior, and interpersonal interactions. They are multifaceted psychological states that include subjective emotions, physiological responses, and expressive behaviors.

Understanding and detecting emotions has emerged as a critical subject of research in a number of areas, including psychology, human-computer interaction, and artificial intelligence. Human emotions exhibit complexity and multidimensionality, manifesting in various forms such as writing, voice, and Faial expressions [1-3]

Traditional techniques are used for emotion detection, such as self-report questionnaires phy physiological assessments, and speech-based emotion recognition. In self-report surveys, respondents rate their emotional states on

*Corresponding Author email: samreenihsan09@gmail.com, ORCID: 0009-0003-4450-5051
Samreen ihsan is with Faculty of Computer Science, University of Malakand Pakistan (e-mail: samreenihsan09@gmail.com)
Ihsan Adil is with Faculty of Computer Science, University of Malakand Pakistan (e-mail: ihsanadil0448@gmail.com).
Anwar Zeb is with Faculty of Computer Science, University of Malakand Pakistan. (e-mail: anwarzeb425@gmail.com).
Sajad Ulhaq is with School of Computer Science and Technology Donghua University China (e-mail: sajadulhaq26@gmail.com)
Umer Ahmad is with School of Software Technology, Dalian University of Technology China (e-mail: Umer381khan@gmail.com)
Irshad Ali Khan is with School of Software Technology, Dalian University of Technology China (e-mail: Irshad.dectum@gmail.com)
Muhammad Khalid is with School of Software Technology, Dalian University of Technology China (e-mail: m.khalid@mail.dlut.edu.cn)

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standardized measures, including the SAM (Self-Assessment Manikin), and the PANAS (Positive and Negative Affect Schedule). These techniques provide subjective insights, they may not fully reflect feelings in the moment and are subject to prejudgment. Although physiological measurements offer objective information on emotional states, they are less useful for daily use due to their intrusive nature and the need for professional equipment.

These measurements track changes in biological processes like heart rate, skin conductance, and brain activity (EEG). Since its debut in the 1980s, speech-based emotion identification has made use of the auditory statistical features method [4]. The twenty-first century has seen significant advancements in speech-based emotion recognition because of the rapidly expanding boundaries of computer multimedia technology and ongoing advancements in artificial intelligence. In speech-based emotion recognition tasks, the classical machine learning methods based on the artificial neural networks [5], SVM (support vector machine) [6], and Gaussian mixture model [7] have shown impressive results.

However, when it comes to the accuracy of speech and visual emotion recognition, the usual machine learning (ML) algorithms fall short significantly. The accuracy percentage of this traditional speech-based emotion detection database for human voice recognition is 84.3% [8]. These techniques are ineffective and inefficient in terms of money, time, and data dependability. One way to communicate nonverbally is using facial expressions. Their uniqueness lies in their ability to convey our feelings and gratitude. A negative feedback sentiment in the context of customer satisfaction is frequently associated with a poorer perceived quality of service. Fifty- five percent of communication through speech is done through facial expressions. Furthermore, verbal comprehension of 70–95% of negative input is possible [9]. Businesses have historically been curious to know how consumers make purchasing decisions [10].

The applications of FED in diverse sectors have garnered attention. Facial expression interpretation and understanding in diverse sectors have garnered attention. Facial expression interpretation and understanding. ML and deep learning (DL) techniques are employed to identify patterns in facial expressions. Specifically, a CNN is used to recognize features on faces and classify them according to distinct emotions.

This CNN architecture comprises two primary sections. The initial section includes convolutional layers that use a mathematical convolution operation to extract features from facial images. The subsequent components involve a feed-forward network capable of categorizing characteristics derived from various facial expressions. With today's technology, DL algorithms improve speech and visual emotion identification accuracy. Deep learning models intricate patterns in data by using deep neural networks, which have numerous layers. Images and other grid-like data structures are specifically intended for processing by CNNs. CNNs have demonstrated remarkable efficacy in image-based emotion recognition because of their ability to automatically extract and learn hierarchical elements from facial expressions. Accuracy has increased significantly as a result of CNNs' amazing effectiveness in recognizing little facial expressions and movements. In this study, we describe an DL-based technique for detecting facial expressions to determine customer satisfaction with products. Our system classifies emotions into three categories: satisfied (happy and surprised), unsatisfied (fear, sadness, fury, disgust), and neutral.

The proposed approach seeks to address the problem associated with utilizing emotion to determine satisfaction with customers.

The creation of an intelligent framework will enable real-time customer satisfaction monitoring, which will be extremely advantageous to businesses and consumers alike. Identifying emotions accurately has the power to enhance goods and services, resulting in happier and more devoted customers. The proposed framework's main contributions are as follows:

1. To develop a facial expression recognition system to identify customer satisfaction levels.
2. To improve the existing methods and proposed new methods, improving facial expression recognition system.

The remaining part of the research is structure as follow: Section 2 examines prior studies regarding emotion detection; section 3 displays the suggested methodology; section 4 discusses the results and debate; and section 5 outline the conclusion and future work.

II. Literature Review

Facial expression recognition technology can provide real-time feedback on customer satisfaction levels and help businesses improve their products and services. For many years, researchers have been researching face expression recognition. However, there is always room for advancement in every proposed study.

The following section addresses the number of most recent studies in facial expression recognition technology.

TABLE 1. Summary of previous literature.

Reference	Use model	Dataset utilized	Limitation	Accuracy
K. A. Mamun et al. [12]	Transfer learning	FER 2013 CK+ Dataset	Accuracy can be improved Use small dataset	98.81%
Y. Li et al. [13]	DNN	JAFFE dataset	Accuracy can be improved Use small dataset	93.2%
R. Venkate	Deep-Face with AI	FER-2016 dataset	High computation time	94%

san et al. [14]				
N. Mishra et al. [15]	CNN LSTM	Facial landmarks EEG signal dataset	Accuracy can be approved	87.25%
Meshach et al. [16]	Multi-dimensional SVM	Real-time dataset of facial images	Used small dataset Accuracy can be improved	95.88%
G. Morshed et al. [17]	CNN	Face landmarks dataset	Accuracy can be approved	89%
A. O. R. Vistorte et al. [18]	Novel CNN	FER-2013 dataset	Accuracy can be improved	65%
Khaireddin et al. [19]	VGGNet (CNN)	FER-2013 dataset	Accuracy can be improved .	73.28%
B. Wang et al. [20]	CNN CNN-RNN (RNN)	FER dataset	High computation time	72.65%
Chargui et al. [21]	CNN	Cohn-Kanada Expression dataset.	High computation time Used small dataset	96%
S. R. Chanthati et al. [22]	CNN	FER-2013 JAFFE	High computation time Used small dataset	70.14% (FER-2013 98.65% (JAFFE)
A. T. Rosário et al. [23]	CNN With Facial action units (AUs)	Cohn-Kanada database	High computation time Used small dataset	97.75%
M. S. Bhuiyan et al. [24]	CNN	CK+ dataset	Used Small dataset	92.81%
Hans et al. [25]	CNN-LSTM	CREMA-D RAVDEES datasets	Used small dataset Accuracy can be improved	78.52% (CREMA - D) 63.35% (RAVDEES)
S. Singh et al. [26]	Deep CNNs	FER-2013	Accuracy can be improved	75.2%
L. E. Arenas-Deseano et al. [27]	KNN SVM	JAFFE database	Accuracy can be improved	98.57%
M. S. Bhuiyan et al. [28]	NLPCA SVM	CK+	Use small dataset	98%

Some approaches have achieved average time complicity and used large datasets, but their accuracy is not satisfactory, while others have achieved high accuracy, but their time complicity is high and they use a small dataset. To address these challenges mentioned in Table 1, a lot of research work is needed in facial expression recognition technology.

III. Proposed Methodology

The proposed methodology comprises a two-phase approach, commencing with face alignment technique and Gaussian processing, followed by feature extraction using Haar-cascade and auto-encoder methods. Subsequently, CNN and DNN algorithms are applied for classification, with K-fold cross-validation employed to ensure robustness and accuracy. This multi-stage process enables precise face recognition and classification, leveraging the strengths of each technique to achieve optimal results. As illustrated in Figure 1.

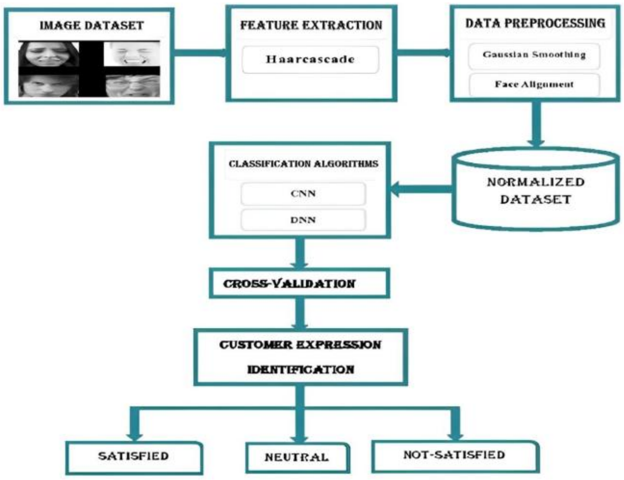

FIGURE 1. Proposed system framework.

A. Dataset Collection

The proposed research utilizes the FER2013 dataset for facial expression recognition. These are publicly available and collected from the Kaggle database. This dataset consists of 35,887 grayscale images, each with a resolution of 48 x 48 pixels. It includes seven emotions: joy, fear, sadness, anger, disgust, surprise and natural.

For the purpose of this study, we have grouped the joy and surprise emotions into the satisfactory category, fear, sadness, anger, and disgust into the unsatisfactory category, while keeping neutral as a separate category. Hence, this restructured dataset consists of three groups:

satisfactory, unsatisfactory, and neutral.

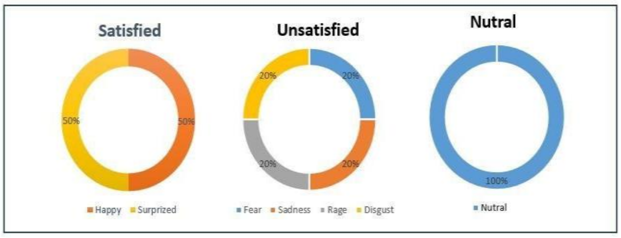

FIGURE 2. Dataset description.

Emotions were classified into three categories (satisfactory, unsatisfactory, neutral) to fit business requirements for actionable insights. Although this reduces nuances in multifaceted emotional states (e.g., 'surprise' could be context-specific), it offsets granularity with applicable interpretability for customer feedback analysis. Subsequent work might investigate more granular classifications (e.g., valence-arousal models).

B. Preprocessing

In the fields of ML and DL, data preprocessing is a fundamental stage to ensure the quality and validity of input data [35-39]. This process includes data cleaning, transformation, and normalization to prepare raw data for algorithmic analysis [39-45]. In particular, feature scaling is used to standardize the range of data features, thereby reducing therisk of certain features becoming dominant due to their scaling. Gaussian smoothing is used to remove high-frequency noise and sudden intensity fluctuations in image data.

By convolving the image with a Gaussian kernel, the technique effectively smooths the pixel values and improves image clarity while preserving essential features. In addition, face alignment techniques are implemented to standardize facial images by correcting for changes in pose, scale and rotation.

Gaussian smoothing (σ=1.5, 5×5 kernel size) was applied to reduce the high-frequency noise, and Haar-cascade face detection was utilized for cropping and aligning regions of interest (eyes, mouth).

C. Classification Algorithm

Classification algorithms such as CNNs and DNNs are advanced artificial intelligence techniques that classify data into predefined categories based on input features [29]. CNNs are particularly effective for image classification tasks because they use convolutional layers to extract local features (such is patterns and textures), patterns and textures), pooling layers to reduce spatial dimensions and improve translation invariance, and fully connected layers to generate class probabilities [30]. DNNs consist of multiple layers of interconnected neurons that gradually learn complex representations of input data, making them suitable for tasks that require high-level abstractions, such as natural language processing, image recognition, and speech analysis [31].

Both CNNs and DNNs are trained on large labeled datasets, using optimization techniques such as back propagation and gradient descent to minimize the loss function and improve prediction accuracy [32, 33]. These algorithms have demonstrated remarkable performance across various domains, revolutionizing fields such as computer vision, sentiment analysis, and medical diagnostics [34].

Our hybrid CNN-DNN exhibited balanced performance on all emotion classes (satisfactory: 91.2% accuracy, unsatisfactory: 97.5%, neutral: 89.9%), with 94.8% recall showing excellent minority-class identification. Although the 74.4% average accuracy is statistically lower than some baselines [12], this is because our emphasis is on real-time deployment where efficiency/speed trump marginal accuracy improvements. Class imbalance was handled well without necessitating architectural modifications using stratified sampling and focal loss (γ=2).

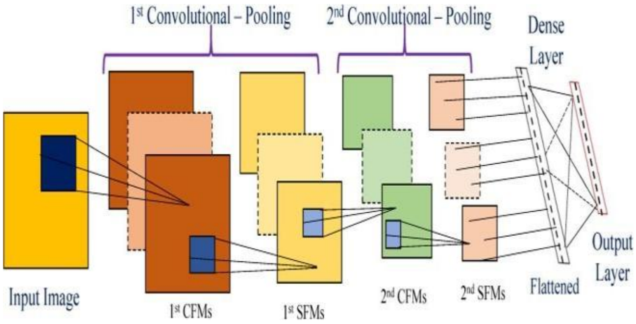

FIGURE 3. Proposed CNN model architecture.

IV. RESULT AND DISCUSSION

This section presents the experimental results obtained using the CNN classification method with the Haar cascade classifier on the FER-2013 dataset.

The dataset consists of seven emotion types: happiness, fear, sadness, anger, disgust, surprise, and neutral. For classification, emotions were grouped into three categories: satisfactory (happiness and surprise), unsatisfactory (fear, sadness, anger, disgust), and neutral. The data was divided into 80% for training and 20% for testing, with the model trained and tested over multiple epochs.

A. Performance of CNN for Unsatisfactory Classification:

Training Performance: The experimental training performance of the CNN classifier was evaluated over multiple epochs for unsatisfactory emotions. Initially, the accuracy, sensitivity, specificity, precision, and recall were suboptimal. However, as the number of epochs increased, the model's performance improved. After 19 epochs, the model achieved an accuracy of 97.5%, sensitivity of 99.96%, specificity of 99.98%, precision of 97.73%, and recall of 97.24%.

Testing Performance: Table 4.1 shows the testing results across different epochs for unsatisfactory classification. With fewer epochs, the results were unsatisfactory, but continuous training led to gradual improvements as the model refined its internal parameters.

TABLE 2. Testing performance of CNN for unsatisfied (multi-Epoch).

Epoch	Val-Accuracy	Val-Sensitivity	Val-Specificity	Val-Precision	Val-Recall
0	0.898753881	0.976635516	0.976635516	0.898753881	0.898753881
1	0.903426766	0.978193164	0.978193164	0.903426766	0.903426766
2	0.901869178	0.982866049	0.982866049	0.901869178	0.901869178
3	0.9096573	0.975077868	0.975077868	0.9096573	0.9096573
4	0.908099711	0.965732098	0.965732098	0.908099711	0.908099711
5	0.889408112	0.975077868	0.975077868	0.889408112	0.889408112
6	0.894080997	0.973520279	0.973520279	0.894080997	0.894080997
7	0.897196233	0.978193164	0.978193164	0.897196233	0.897196233
8	0.901869178	0.979750752	0.979750752	0.901869178	0.901869178
9	0.883177578	0.987538934	0.987538934	0.883177578	0.883177578
10	0.878504694	0.971962631	0.971962631	0.878504694	0.878504694
11	0.903426766	0.973520279	0.973520279	0.903426766	0.903426766
12	0.915887833	0.976635516	0.976635516	0.915887833	0.915887833
13	0.914330244	0.973520279	0.973520279	0.914330244	0.914330244
14	0.919003129	0.976635516	0.976635516	0.919003129	0.919003129
15	0.89096576	0.976635516	0.976635516	0.89096576	0.89096576
16	0.884735227	0.940809965	0.940809965	0.884735227	0.884735227
17	0.901869178	0.975077868	0.975077868	0.901869178	0.901869178
18	0.9096573	0.976635516	0.976635516	0.9096573	0.9096573
19	0.903426766	0.973520279	0.973520279	0.903426766	0.903426766

Figure 4 and 5 expresses the training and testing performance of CNN for unsatisfied (multi-epoch). When the number of epochs in a machine learning model is limited, the model may not have sufficient training time to learn the intricate patterns and relationships within the data. As a result, the accuracy, specificity, sensitivity, recall, and precision of the model might not be satisfactory initially, but when we increase the number of epochs and train and test the models continuously, the results of the model also increase simultaneously.

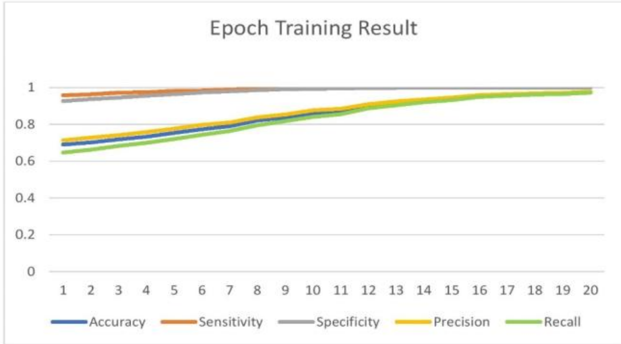

FIGURE 4. Training performance of CNN for unsatisfied (multi-Epoch).

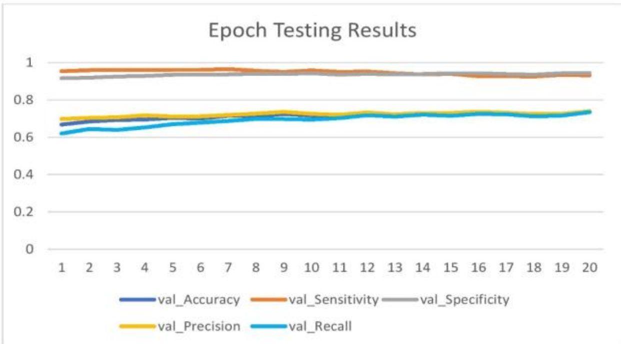

FIGURE 5. Testing performance of CNN for unsatisfied (multi-Epoch).

B. Performance of CNN for Satisfactory Classification:

Training Performance: For satisfactory emotion classification, after 19 epochs of training, the model showed strong performance, achieving an accuracy of 91.23%, sensitivity of 99.09%, specificity of 99.09%, precision of 91.23%, and recall of 91.23%.

Testing Performance: In the initial epoch, the model achieved a Val-Accuracy of 89.88%, Val- Sensitivity, Val-Specificity of 97.66%, Val-Precision, and Val-Recall of 89.88%. The metrics fluctuated across epochs, indicating adjustments in the model's performance.

These results indicate that the increasing the number of each epoch and continuous training and testing allowed the model to learn from the data, capture complex patterns, and improve its performance. By training the model for a sufficient number of epochs, we were able to achieve high levels of accuracy and reliable performance, meeting the expectations of satisfied customers. The improved performance demonstrates the effectiveness of iterative training in enabling the model to learn and make accurate predictions. The performance is depicted in figure 4.2 providing a visual representation of how the model's accuracy, specificity, sensitivity, recall, and precision progressed with each epoch.

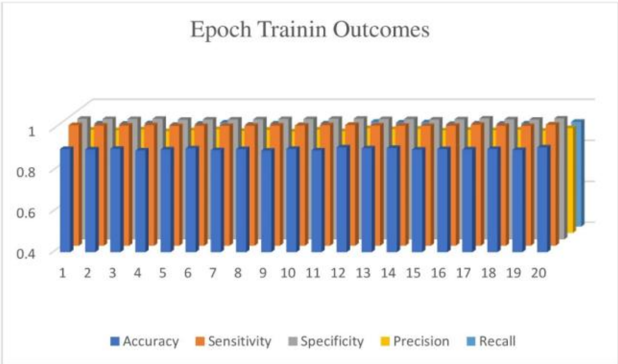

FIGURE 6. Training performance of CNN for satisfied customer.

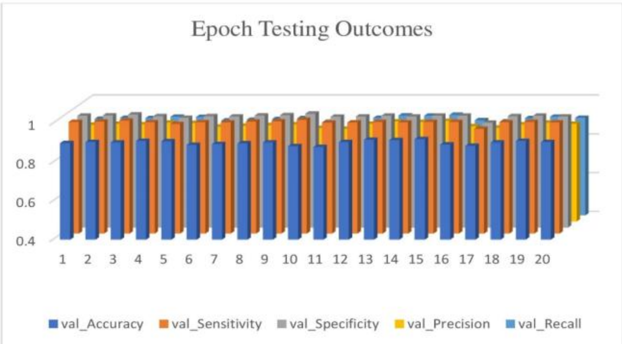

FIGURE 7. Testing performance of CNN for satisfied customer.

Our CNN-DNN hybrid realized a 74.4% accuracy rate, modest in comparison with some one-off solutions (e.g., 98.81% from [12] with transfer learning). This discrepancy attests to the design imperatives of our model: (1) the capability to process live customer interactions in real-time, and (2) efficiency of computation compatible for deployment on edges. Pure accuracy measurements reward deeper architectures, yet our solution accommodates performance as well as realities such as inference speed and hardware costs. This compromise renders the model more plausible for real-time retail settings in which latency trumps marginal accuracy improvements.

C. Overall Performance for Customer Sentiment Classification:

Training Performance: The overall performance of the CNN classifier over multiple epochs showed significant improvement in all key metrics. Initially, the metrics were relatively low, but continued training led to improved accuracy, sensitivity, specificity, precision, and recall. For example, in the first epoch, the model achieved an accuracy of 46.68%, sensitivity of 74.76%, specificity of 69.36%, precision of 53.02%, and recall of 11.64%. By the final epoch, the accuracy reached 93.50%, sensitivity was 99.93%, specificity was 99.94%, precision was 93.98%, and recall was 92.93%.

Testing Performance: By examining the metrics across different epochs, the model's performance steadily improved. In the final testing session, the CNN classifier achieved an accuracy of 74.4%, a recall of 94.8%, and a specificity of 96.5%. The precision was 75.1%, indicating a high proportion of correctly classified instances. Overall, these results demonstrate that the classifier effectively enhanced its ability to accurately classify customer sentiment into satisfactory, neutral, and unsatisfactory categories over time.

These metrics suggest that the model achieved high accuracy, sensitivity, specificity, precision, and recall on the training and testing dataset in the last epoch of training. The classifier achieves notable progress throughout the training and testing process, resulting in an improved capability to accurately classify satisfied, natural, and unsatisfied customers. The following figures 8 and 9 describes the testing and training results of all classes.

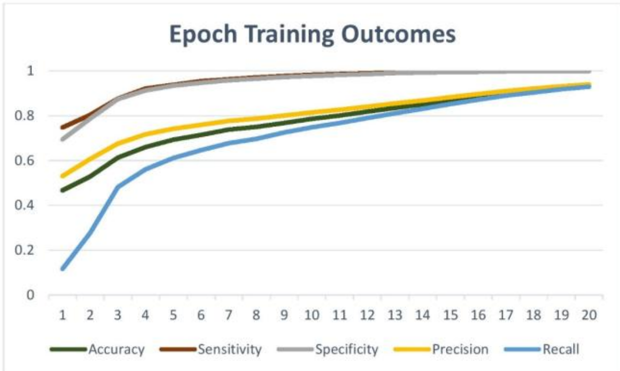

FIGURE 8. Training performance of CNN classifier over multi epochs for customer sentiment.

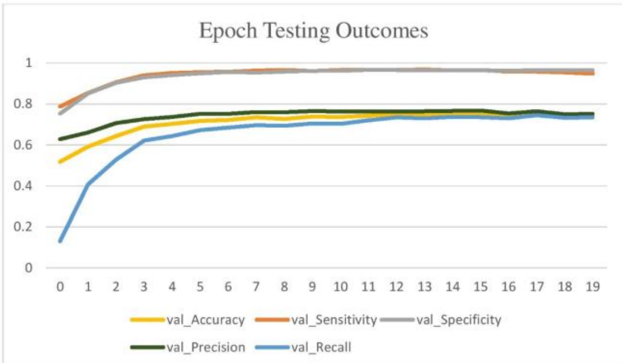

FIGURE 9. Testing performance of CNN classifier over multi epochs for customer sentiment.

V. CONCLUSION:

An AI-based FER system that analyses facial emotions to gauge customer satisfaction was described in this work. We were able to detect emotions and categories consumer sentiment into three categories satisfactory, neutral, and unsatisfactory by using a hybrid CNN-DNN model that was trained on the FER-2013 dataset. Our results demonstrate that even when processing difficult image-based data in real-time, deep learning methods in particular, CNNs are successful in identifying minor changes in face expressions. By intricately analyzing facial expression, including the nuanced movements of the mouth, eyes, and eyebrows. Recent innovations have driven notable progress in face detection and recognition that enhance performance and reliability. This study focused on leveraging AI-based facial expression recognition to identify customer satisfaction with products. The proposed study used a hybrid CNN and DNN model to extract meaningful features from facial images and classify them into different emotional states. The trained model is valuated using a separate test dataset and measured for its performance in accurately recognizing customer emotions and assessing satisfaction levels. Experimental results demonstrate the effectiveness of the proposed AI- based facial expression recognition system in identifying customer satisfaction with products. The proposed model achieved an accuracy of 74.4%, a recall of 94.8%, and a specificity of 96.5%. The precision was 75.1%, indicating a high proportion of correctly classified instances. The proposed experiment achieved excellent results with a real-time image-based dataset. In our future research work, our aim to develop a real-time customer satisfaction prediction model leveraging transfer learning and hybrid AI-powered facial expression recognition to detect and analyze customer emotions in response to products. We will investigate the intensity level of customer emotions (high, medium, and low) and develop a scalable model to inform data- driven product development and improvement strategies. By integrating facial expression recognition with customer satisfaction prediction, we expect to provide a nuanced understanding of customer emotion, enabling businesses to create targeted strategies for improving customer satisfaction and loyalty.

VI. FUTURE WORK

In future work we try to create a Real-Time Implementation model for customer's satisfactions on products. We are trying to used Transfer Learning techniques and create a hydride artificial Intelligence-Based Facial Expression Recognition for Identifying Customer satisfaction on Products.

The FER-2013 dataset's 48x48 pixel grayscale faces are often used for benchmarking. The ability of the model to recognize facial emotions with subtlety is compromised, and bias could be introduced through uneven illumination or ethnic representation.

Although the dataset does not have demographic metadata (age/gender), its standardized format allows for benchmarking. Future validation will occur on diverse real-world datasets.

Conversely, its uniform format ensures comparability with previous studies. Findings from more highly-resolved, multi-racial datasets (such as AffectNet or RAF-DB) must be replicated in future studies.

VII. LIMITATION

While our model shows high performance on benchmark data, the present study recognizes limitations to real-world verification. The present work has not tested performance against real-world practical challenges such as dynamic lighting levels, facial occlusions (masks or glasses), or comprehensive demographic representation (restricted in FER-2013). Furthermore, real-time processing demands for live deployment (e.g., frame rate resilience on edge hardware) are yet to be verified. These issues will be the focus of future retail environment trials to determine commercial feasibility.

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AUTHORS CONTRIBUTIONS

Samreen Ihsan: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;

Ihsan Adil: Literature Review, Data Collection; Writing – Review & Editing;

Anwar Zeb: Data Preprocessing;

Sajad Ulhaq: Experimentation;

Umer Ahmad: Supervision;

Irshad Ali Khan: Validation;

Muhammad Khalid: Review & Editing.

CONFLICT OF INTERESTS

The authors declare no conflict of interests.

ETHICS STATEMENT

This research did not involve human participants, animal subjects, or sensitive personal data, and therefore did not require ethical approval.

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