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Emotion Analysis from Customer Shopping Experience using ML

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Abstract: Understanding how customers feel is one of the most valuable insights a business can gain. Traditionally, companies depend on surveys, ratings, or written feedbacks to collect reviews—but these methods are often time-consuming, biased, or ignored by users. With the rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML), it is now possible to automatically detect and interpret human emotions using technologies like facial recognition, video analysis, and Natural Language Processing (NLP). This paper presents a comprehensive survey of the latest research efforts aimed at improving customer feedback systems using AI-powered emotion recognition. Many researchers try to understand emotions such as happiness, sadness, anger, or curiosity by studying people's facial expressions, often using images or videos taken from cameras or webcams. Popular techniques include Convolutional Neural Networks (CNNs) for image-based emotion classification, Support Vector Machines (SVMs) for quick categorization, and Recurrent Neural Networks (RNNs) like GRU and L.This document gives formatting instructions for authors preparing papers for publication in the Proceedings of an IEEE conference. The authors must follow the instructions given in the document for the papers to be published. You can use this document as both an instruction set and as a template into which you can type your own text.

Keywords: Emotion Recognition, Facial Expression Recognition, Machine Learning, CNN, Viola-Jones Algorithm

I. INTRODUCTION

In today's fast-moving world of online shopping and smart retail, understanding how customers feel has become crucial for improving their experience and making better business decisions. Traditional feedback methods like surveys or star ratings don't always give a complete picture of a customer's true emotions. That's why Facial Expression Recognition (FER) and Machine Learning (ML) are becoming important tools—they can detect and analyse emotions in real time without needing customers to say anything.

People's facial expression usually says a lot about how they feel. Using Artificial Intelligence (AI), these expressions can be analysed automatically. This process involves three main steps: first, the system detects a person's face using the Viola-Jones algorithm; second, it extracts important facial features; and finally, it uses a Convolutional Neural Network (CNN)—a powerful deep learning model—to recognize emotions like happiness, sadness, anger, fear, surprise, and more.

This research builds a real-time AI system that can analyse customer emotions while they shop in places like malls, supermarkets, or service centres. The goal is to help businesses better understand customer mood and satisfaction, so they can adjust services accordingly.

By combining computer vision and deep learning technologies, this project supports the growing field of affective computing—where machines can understand human emotions. This approach makes it easier and quicker to understand how people feel, allowing businesses to tailor their services and improve the overall customer experience.

II. LITERATURE SURVEY

The literature reviewed spans a diverse set of methodologies and technologies applied in the field of emotion recognition. In

[1] Shail Kumari Shah introduce a system called Emotica.AI that detects customer emotions in real-time using a camera. It combines Viola-Jones algorithm for face detection and Convolutional Neural Networks (CNN) for classifying emotions like happy, sad, angry, etc. The model was using a large dataset and achieved around 76% accuracy. It supports recognizing multiple faces all once. Built using OpenCV, Keras, and Python libraries like Tkinter, it aims to automate the feedback process in businesses. Instead of asking for ratings or reviews, it captures emotional responses directly from customer faces. The in put images are 48x48 pixels and are standardized before being processed. This helps companies quickly understand customer satisfaction. The system's real-time capability makes it practical for malls and public 2 service counters. It eliminates the need for manual review analysis.

In [2] Chirag Bera and his colleagues discuss about research that uses facial expressions to evaluate how interested a customer is in a product. It uses live or recorded video to capture the face and then analyzes eye and mouth regions. By calculating something called a “curious ratio”, the system estimates if someone is interested, neutral, or disinterested. The method involves preparing the image, identifying key features from it, and then determining the emotion being expressed. It also uses face registration and geometric normalization techniques. A deep learning neural network is used to interpret expressions. The study also considers how long a customer looks at a product for further insights. This can be applied in retail to better understand product appeal. It mimics how humans read emotions through subtle facial movements. The solution is accurate and adaptable for in-store product evaluations.

In [3] Rifat Hasan and his team discuss about the fact that focused on creating full customer reviews using Natural Language Processing (NLP) and AI. Instead of relying on customers to write reviews, it turns survey data (like ratings) into sentences. Techniques like TF-IDF, tokenization, and part-of-speech tagging are used. It helps convert structured data into human-like language using pretrained NLP models. The system ensures grammar and sentiment alignment in generated reviews. It was tested in shopping malls where direct feedback is usually limited. Review quality closely matches human-written reviews. The approach can be extended to use voice inputs in the future. It also proposes using advanced models like BERT or GPT for better naturalness. Helps businesses understand customer sentiment without extra effort from users.

In [4] DNVSLS Indira and team propose a method named MFER to predict customer satisfaction using facial expressions. It involves face detection, facial feature extraction, and finally emotion classification. The system combines a Deep Convolutional Neural Network (CNN) with the Haar Cascade Classifier to detect faces and recognize facial expressions. It recognizes changes in facial muscles to decide if someone is satisfied or not. The facial features are analyzed geometrically, and responses are categorized into emotions like happy or sad. The method is much faster and more reliable than traditional feedback forms. It compares well against SVM classifiers and shows better results. It can be effectively used in areas like business, education, and customer support to better understand and respond to people’s emotions. The model also detects subtle changes in user emotion based on facial movements. This helps in making real-time product or service recommendations.

In [5] Kitti Koonsanit and Nobuyuki Nishiuchi present a way to evaluate customer satisfaction based on facial expressions, age, and gender using machine learning. It collects data through a webcam while customers use a product or service. Emotions are classified using algorithms like SVM, KNN, Logistic Regression, and MLP. About 84% accuracy was achieved for seven emotions. Each expression like happy, angry, or sad is scored based on its intensity (0–100). The system is trained in Google Colab using Python. It enables emotion-based product or service evaluations without customers filling surveys. Real-time feedback is captured through video streaming. Helps product designers and businesses measure satisfaction more naturally. It’s a useful solution for integrating emotion data into digital interfaces.

In [6] Deepak Gupta and his colleagues focus on analyzing text feedback using CNN and GRU, both deep learning models. It classifies customer messages as positive, negative, comment, complaint, etc. Since neural networks need inputs of fixed size, feedback texts are padded. The convolutional layer captures common patterns (n-grams), and the GRU layer helps with understanding word sequences. Datasets used were from Microsoft Office users in four languages. The model handles multiple labels per sentence by duplicating entries. Accuracy was good across languages like English and French. Future improvements can come from larger, more diverse datasets. It automates customer support by analyzing written opinions instantly. This saves time and helps businesses respond faster to complaints or compliments.

In [7] Abdelalim Sadiq and his team predict whether a customer is satisfied, neutral, or unsatisfied using geometric facial features. It uses a camera to capture customer faces, then calculates the distances between points like eyes, nose, and mouth. An SVM classifier was used to identify emotions, and the system showed strong performance when evaluated on the JAFFE dataset. It simplifies emotions into 3 categories to help understand customer reactions better. Future versions might add features like eye tracking or gaze analysis. Helps in evaluating products and customer experience without asking questions. The goal is to interpret emotions automatically using only face images. It's efficient for shopping environments and feedback stations.

In [8] Zolidah Kasiran and Saadiah Yahya (Dr) discuss how facial expressions—especially those involving the eyes and mouth—can be used to measure customer satisfaction. It suggests that traditional feedback (like surveys) doesn’t fully capture emotions. The system captures subtle emotional cues from the face during customer interactions. It can adapt to various head angles— whether someone is facing forward or turned to the side—so it stays accurate in detecting emotions. The approach focuses on real-time emotion tracking during live service interactions. The work supports the idea of affective computing, where systems react to human emotions. It helps companies better understand customers without requiring verbal feedback. This approach is adaptable and performs effectively across different settings, whether it's a face-to-face service desk or an online customer support platform. It’s useful for companies wanting to improve service quality based on real emotional responses.

In [9] A.S. Sebyakin and A.V Zolotaryuk propose an AI system that recognizes emotions even under poor lighting or low- quality images. It uses two kinds of features: location (where facial parts are) and shape (how they look). These are extracted from the image’s brightness data using adaptive thresholding and edge detection. A 3-layer neural network then classifies the emotional state. The system processes data in real-time and can be deployed on servers or edge devices (like mobile chips). The model was trained through standard deep learning steps like image augmentation, normalization, and backpropagation. It's suitable for customer service, where quick emotion detection is key. Performs reliably even when the face is partially hidden . This makes it practical in real-life environments with varied conditions.

In [10] Miss Preeti Thakre and team propose combined analysis of facial expressions and text reviews to detect customer emotions. Developed an Emotion-Semantic CNN (ECNN) capable of interpreting emotions expressed through both text and emoticons in user feedback. To classify emotions, it uses SVM and CNN models. The model achieved around 85% accuracy. Works well even when customers use emojis instead of full sentences. The system is capable of examining Amazon product reviews to uncover the emotions behind customer feedback. Also identifies subtle facial changes like wrinkles or muscle movements. It's capable of building user emotion profiles for personalized marketing. Future versions aim to process images or videos uploaded by users. Helps businesses interpret emotions even from short or vague reviews.

In [11] Himanshu Sharma and team design a smart review system that checks if the reviewer is a visitor or an employee. It uses the Haar Cascade algorithm to locate faces in an image, and then applies the Local Binary Pattern Histogram (LBPH) method to recognize and match individual identities. The goal is to avoid fake or biased feedback by staff. Once a face is verified as a visitor, the system captures facial expressions to detect emotions. The entire system operates on a Raspberry Pi, which keeps it compact, cost-effective, and easy to deploy in various settings. The model is built using Keras, with TensorFlow serving as the underlying engine for its AI computations. Emotions like happy, neutral, or angry are recognized and logged. The approach helps businesses collect honest, emotionbased reviews. Works well in locations like restaurants, malls, or public venues.

In [12] Mariem Slim and colleagues propose a method to measure customer satisfaction using six key facial features. The system mainly concentrates on recognizing facial expressions such as happiness, neutrality, and surprise. Used OpenFace and FACS (Facial Action Coding System) for analyzing muscle movements. Also tested the method on advanced datasets like CK+ and Radboud. The system classifies emotion using a mix of machine learning and deep learning techniques, including concepts of Convolutional Neural Networks (CNN),Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). It doesn't depend on camera angle, making it usable in various environments. It analyses distances between specific facial landmarks to interpret and identify a person’s emotional state. Works well in real-time settings, like customer interviews or product testing. Adds emotional insight to product design and user feedback systems.

In [13] Vikrant Chaugule and his team uses a modified Harris algorithm to quickly detect facial features like eyes and mouth. It then calculates a “curious ratio” to measure how interested a customer is. A Bezier curve is used to analyze mouth curvature and decide whether the emotion is positive or negative. The score is then converted into a product review on a scale of 1 to 10. Face detection is done using Viola-Jones, and the analysis works on live or recorded video. Helps stores evaluate product appeal by watching customer reactions. It reduces processing time while maintaining accuracy. Also suggests future use in online shopping to predict customer interest.

In [14] Golam Morshed and team discuss about the capturing of spontaneous facial expressions while customers view products. The system is designed to identify three key emotions—happiness, sadness, and neutrality—by using a combination of CNN with SVM and CNN with Softmax classifiers. Tested with 53 participants, the setup used a digital camera recording at 30 frames per second. Achieved accuracies of up to 89%. The system was built using common hardware (Intel i5 + 8GB RAM). It’s ideal for real-time analysis in stores or product testing labs. Plans to expand the system to detect more emotions like anger or surprise. Helps businesses see how people emotionally react to products without asking them.

In [15] Maria Grazia Violante and colleagues introduce an emotion-based design approach using 3D facial recognition and depth cameras. The method maps customer facial expressions during interviews to emotional needs. Uses SVM to classify emotions and QFD (Quality Function Deployment) to translate them into product features. Employs Russell’s emotion model to assign numerical scores to emotional responses. This process helps create products that match real emotional needs. Uses infrared pattern projection to build accurate 3D face maps. Works best at close range (0.2– 1.5 meters). Emotions are recorded frame-by-frame for high precision. Suitable for agriculture, retail, and consumer product development.

In [16] Wafa Mellouk and Wahida Handouzi review recent work on Facial Emotion Recognition (FER) using CNN and CNNLSTM. It explains how models are moving from detecting basic emotions (like joy, anger) to more complex, real-life ones. Highlights the need for multimodal systems that combine audio, video, and physiological signals. Future developments are likely to incorporate emotion fusion models, which combine multiple emotional cues for improved accuracy. There's also a strong recommendation to build larger and more diverse datasets to enhance the performance of deep learning models. Also notes that most current systems are limited by dataset quality and emotion diversity. Encourages researchers to combine multiple inputs for better emotion understanding.

In [17] Sivakumar Depuru and his colleagues develop a 2-layer CNN model to detect seven facial emotions using the FER dataset. Includes emotions like happy, sad, disgusted, angry, surprised, fearful, and neutral. Achieved 86.05% accuracy using Adam optimizer for learning.

The model was tested for both training and validation, showing good generalization. Future versions aim to analyze video sequences instead of static images. It can be effectively used in real-time feedback systems, helping improve service quality and enhancing learning experiences in educational settings by understanding users' emotional responses. Can be integrated with smart devices for interactive emotional response systems. Emphasizes the importance of recognizing emotions for customer experience and service improvement.

In [18] Amit Pandey and team has created a CNN-based model that removes background noise from images to focus only on facial features. Improved emotion recognition by analyzing eyes, eyebrows, and mouth. Works in both controlled labs and real- world settings. Suggests future use in robotics, healthcare, and security systems. Can be extended to detect emotions from speech or body language.

It is well-suited for Human-Robot Interaction (HRI), enabling machines to understand and react to human emotions, making interactions more natural and responsive. Model performed well on various emotion datasets. Helps make machines more emotionally aware and responsive.

In [19] Zi-Yu Huang and colleagues analyze how CNN models learn which facial parts matter most for recognizing emotions. Found that mouth and nose provide the most emotion information, while eyes and ears contribute less. Used transfer learning on Affect-Net and RAF-DB datasets. Achieved higher accuracy after applying pretrained weights. Accuracy reached 77.37% in some tests. The findings highlight that using larger and more diverse datasets during training significantly improves the system’s overall accuracy and reliability. Helps design better FER models that behave more like human observers. Encourages focusing on mouth region in future emotion classifiers.

In [20] Pawel Tarnowski and team achieved 96% accuracy in emotion recognition using MLP (Multi-Layer Perceptron) models. Tested under fixed conditions using Kinect cameras. Accuracy dropped to 73% when data was split naturally by user groups. The system is capable of identifying seven fundamental human emotions, such as joy, fear, and others commonly expressed through facial cues. Showed that real emotional responses are harder to classify due to variation. Useful for controlled environments like labs or fixed kiosks.

Highlights the importance of facial expression consistency for better accuracy. This technology has potential applications across various fields, including retail for customer experience insights, healthcare for monitoring patient emotions, and gaming to create more immersive and responsive experiences.

A. Summary of Literature Survey

From this literature survey it is evident that, the facial expression recognition system presents a robust face recognition model based on the mapping of behavioural and physiological biometric variables.

The physiological properties of the human face that are relevant to various expressions such as pleasure, sorrow, fear, anger, surprise, and disgust are linked to geometrical structures that are reconstituted as the recognition system’s basis matching template. This work focuses on analyzing live facial expressions of consumers who are viewing a certain product, allowing us to conduct a real-time assessment of that product and score it based on the customer’s facial expression analysis results. This product rating will assist the business owner in increasing product sales while also ensuring that the top items are available for his clients. This feature is significantly more accurate and quicker than previous techniques, which had a greater margin of error..

B. *Table of Summary*

Paper No.	Title	Authors	Techniques Used	Focus Area	Remarks	Limitations
[1]	Emotica.AI	Shail Kumari Shah	Viola-Jones, CNN, OpenCV, Keras	Real-time emotion detection	Automates feedback via facial emotion	76% accuracy; needs good lighting
[2]	Curious Ratio System	Chirag Bera, Prathmesh Adhav, Shridhar Amati	Image preprocessing, face registration, deep neural network	Customer interest detection	Mimics human-like interpretation	Relies on eye/mouth clarity
[3]	NLP Review Generator	Rifat Hasan, S M Nahid Hasan, Anika Tasnim Islam, Fauzia Yasmeen	NLP, TF-IDF, POS tagging, pre-trained models	Textual review generation from ratings	Human-like reviews from raw data	Limited without voice input
[4]	MFER Method	DNVSLS Indira, L Sumalatha, Babu Rao Markapudi	Deep CNN, Haar Cascade	Emotion detection via facial expressions	Outperforms SVM models	Needs training for subtle emotions
[5]	Multimodal Emotion Recognition	Kitti Koonsanit, Nobuyuki Nishiuchi.	SVM, KNN, Logistic Regression, MLP	Age/gender-aware emotion classification	84% accuracy, intensity-based scoring	Survey replacement is partial
[6]	Text Feedback Classifier	Deepak Gupta, Pabitra Lenka, Harsimran Bedi, Asif Ekbal, Pushpak Bhattacharyya	CNN, GRU	Text sentiment classification	Works across 4 languages	Needs padding, limited to written text
[7]	Geometric Emotion Detection	Abdelalim Saliq, Moulay Smail Bouzakraoui, Abdessamad Youssfi Alaoui	SVM, facial geometry	Satisfaction prediction via facial points	Efficient for 3 emotion classes	Limited emotion diversity
[8]	Eye-Mouth Focused FER	Zolidah Kasiran, Saadiah Yahya (Dr)	Real-time tracking, pose adjustment	Facial emotion analysis in service areas	Flexible and works in real-time	Emotion subtlety detection varies
[9]	Low-Light Emotion Detector	A S Sebyakin, A. V. Zolotaryuk	Edge detection, adaptive thresholding, 3-layer NN	FER under poor image conditions	Works in low-light/partial occlusion	Lower accuracy for subtle emotions
[10]	ECNN System	Miss. Preeti Thakre, Prof. Dr. Pankaj Agarkar	ECNN, CNN, SVM	Multimodal analysis (text + image)	85% accuracy; emoji detection too	Limited for video-based reviews
[11]	Smart Review System	Himanshu Sharma, Devang Sharma, Krutarth Bhatt, Bhavya Shah	Haar Cascade, LBPH, Keras	Identity-aware emotion feedback	Filters biased staff reviews	Face recognition not always reliable
[12]	FACS-Based Emotion Model	Mariem Slim, Rostom Kachouri, Ahmed Ben Atitallah	OpenFace, FACS, CNN, SVM, KNN	Feature-based satisfaction estimation	Works well in interviews/product testing	Fewer emotions used (3 categories)
[13]	Curious Ratio with Bezier	Vikrant Chaugule, Abhishek D, Aadheeshwar Vijayakumar, Pravin Bhaskar Ramteke.	Modified Harris, Bezier curve	Customer interest from video	Converts facial cues to ratings	Focused on specific regions only
[14]	Spontane ous	Golam Morshed,	CNN-SVM,	Real-time facial	89% accuracy; tested on 53	Emotion range limited (3

	Emotion Capture	Hamimah Ujir, Irwandi Hipiny	CNN-Softmax	expression tracking	users	classes)
[15]	Emotion-Based Product Design	Maria Grazia Violante, Federica Marcolin, Enrico Vezzetti, Luca Ulrich, Gianluca Billia and Luca Di Grazia	3D facial recognition, SVM, QFD	Mapping facial emotion to design	High precision with depth cameras	Effective only at close range
[16]	FER Survey	Wafa Mellowk, Wahida Handouzi	CNN, CNN-LSTM	Trends in FER research	Emphasizes multimodal fusion	Relies on datasets' quality
[17]	2-Layer CNN Model	Sivakumar Depuru, Anjana Nandam, P.A.Ramesh,M. Sak tivel, K.Amla, Sivanantham	CNN, FER dataset	Seven-emotion recognition	86.05% accuracy, real-time usable	Limited to static images
[18]	Emotion from Cleaned Features	Amit Pandey, Aman Gupta, Radhey Shyam	CNN, noise filtering	Enhanced facial feature analysis	Useful in HRI and healthcare	Only facial data, no audio input
[19]	Facial Part Sensitivit y	Zi-Yu Huang , Chia- Chin Chiang , Jian-Hao Chen , Yi-Chian Chen , Hsin- Lung Chung , Yu-Ping Cai & Hsiu-Chuan Hsu	CNN, Transfer Learning	Importance of facial regions in FER	Mouth region found most critical	Limited data diversity
[20]	Kinect- Based FER	Paweł Tarnowski, Marcin Kołodziej, Andrzej Majkowski, Remigiusz Rak	MLP, Kinect	FER in fixed environments	96% lab accuracy; 73% natural data	Sensitive to user variance

III. CONCLUSIONS

In today's experience-driven market, simply offering quality products is no longer enough understanding how customers truly feel has become just as important.

This paper explored various research efforts that use artificial intelligence and facial expression recognition to decode human emotions in retail settings. From analyzing subtle facial muscle movements to interpreting textual feedback, these systems provide a deeper, more natural understanding of customer satisfaction.

Through our study and literature review, it is evident that real-time emotion recognition powered by Convolutional Neural Networks (CNNs), Viola-Jones face detection, and other machine learning methods offers a powerful alternative to traditional feedback systems. These technologies are capable of capturing honest, unbiased emotional responses without requiring verbal input from the customer. They reduce the reliance on manual surveys and help businesses gain faster, data-driven insights into customer preferences and reactions.

Ultimately, this paper supports the growing shift toward *affective computing*—where machines don't just process data, but understand feelings. By integrating such emotion-aware systems into customer experience strategies, businesses can not only improve satisfaction but also build stronger, more empathetic relationships with their users.

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