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A Survey Paper on Emotion based Age Separated Customer Feedback System using CNN

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Abstract:- Humans use their emotions to express their feelings. There are numerous methods for people to communicate their feelings, including through body language and facial expressions. The most potent and common way for people to express their emotions through facial expression. CNN and a deep learningbased approach are both used in this work. Our goal is to built an emotion-based age-separated customer feedback system that enables businesses to improve their operations by better understanding the needs of customers of all ages. In this paper, we primarily examined the prior literature that has been published on emotion analysis in an effort to identify knowledge gaps and potential directions for future research.

Keywords: *CNN, Customer Feedback, Age-Separate, Emotion Recognition, Machine Learning, Deep Learning.*

I. INTRODUCTION

When deciding whether a product or service satisfies the needs of the consumer, client feedback is a crucial consideration. Nowadays, a lot of businesses compete with one another to raise the caliber of their goods and services by carrying out customer satisfaction surveys using forms, phone interviews, etc. However, not all customers responded to the survey with comments. The supplied survey's veracity is also not guaranteed. In nonverbal communication, facial expressions are employed. They provide us with a unique platform to convey our feelings of gratitude and emotion. So we can receive correct feedback by identifying emotions.

People in real life display their emotions on their faces to display their psychological processes and attitudes in social interactions. This project's main goal is to identify the emotion that an input image with a single facial expression belongs to.

Emotion recognition can be precisely divided into the classification of basic emotion and the classification of compound emotion due to the complexity of interpreting a human face.

The emotion recognition problem requires an algorithm to perform feature extraction and categorical classification, much like all other classification tasks.

We need to develop a model that can categorize the input depending on the feature after extracting a certain feature from the data in order to classify an emotion. These are the steps:

- *Pre-processing of Data:*
  The purpose of data pre-processing is data standardization. The usual method is to divide the data by the standard deviation and set the data's mean to 0.

- *Extracting Features:*
  The standard procedure is to identify faces and extract Action Units (AU) from them; some emotions comprise combinations of AUs that are coded as features.

- *Model Development:*
  A traditional classifier can use an unsupervised algorithm or a supervised method. Support Vector Machine is a classic example of a supervised algorithm, and Principle Component Analysis (PCA) and Linear Discriminant Analysis are examples of unsupervised algorithms.

- *Generation of Labels or Results:*
  To construct a label or result, one often looks for the decision boundary that is closest to the data in Euclidean space.

The Problems with the Conventional Approach are:

- *Light Variance:*

The intra-class noise of lights will affect the model to categorise the emotion because each image is taken in a completely different background and lighting situation. As a result, the effect of lighting noise may cause the same sort of feelings to be categorised in different ways.

- *Locational Variation:*

The location of the feature may consequently have an impact on the functionality of the feature extraction since the feature is often extracted by filters like the application of Local Binary Pattern. If the face is rotated or located in a different area of the image, the AU may be retrieved inaccurately as a result.

The two flaws mentioned above are the two biggest drawbacks with traditional algorithms. The solution is to use the algorithm of to solve the problems of the conventional approaches. The main distinctions between using a Convolutional Neural Network (CNN) algorithm and a conventional approach are:

- Automatic Feature Extractor Generation:

Because feature extractors are created during the training process based on the provided ground truth, features of images can be automatically captured without the usage of users' built-in feature extractors.

- *Variations in the Mathematical Model:*

They are commonly referred to as ”Linear Classifiers” because the standard approach entails doing classification using a linear transformation. To distinguish between variations in the classification process, CNN and other Deep Learning algorithms frequently mix the linear transformation with nonlinear functions like the sigmoid (Logistic Function) and Rectified Linear Unit (ReLU).

- *The more Subtle Structure:*

The traditional approach often only conducts one layer of action; the SVM, for instance, only has one set of weights. However, CNN and other deep learning algorithms classify data using many layers of processing.

In order to determine how to implement our own project, "Emotion based age separated customer feedback system," we will classify and analyse a variety of different research papers written by various individuals who used CNN in their projects. We will also compare the techniques used by them and weigh the benefits and drawbacks of those methods.

II. MOTIVATION

Businesses have a significant impact on how customers perceive their goods and services, as has been noticed during the past ten years. Today's consumers have more options than ever. Having the best goods or the lowest costs is frequently insufficient today. Instead, businesses must concentrate on inspiring pleasant feelings in their customers in order to inspire enduring loyalty and brand advocacy. Emotions have a big impact on how we live our lives and what choices we make. Through verbal and non-verbal clues, organisations can use emotion recognition to better understand the attitudes and behaviours of their consumers. Customer satisfaction can be assessed manually using techniques like focus groups, interviews, and satisfaction surveys. These approaches are not cost, time-, and data-reliability-efficient and effective. The use of facial expressions is a form of nonverbal communication. They provide us with a unique means of expressing our feelings and gratitude. A negative feedback sentiment is frequently linked to a lower perceived level of service quality in the context of customer satisfaction. A speech is communicated with the face to the extent of 55 percent. Additionally, 70 to 95 percent of unfavourable comments can be understood verbally. Understanding how consumers decide what to buy has always been of interest to businesses.

III. LITERATURE SURVEY

In the paper ”Emotion Recognition using Convolutional Neural Networks,” the authors propose a deep learning system to identify one of the seven fundamental human emotions based on a given photograph of a person's facial expression. Using transfer learning from an existing pre-trained model, the team performs tasks such as data pre-processing, data augmentation, model testing, training, prediction, and assessment. They employ convolutional neural networks (CNNs), a deep learning method that combines feature extraction and classification, to build a classification model. To save time, the team modifies an existing model, VGG, trained by the University of Oxford, and uses the JAFFE and CK+ datasets. However, the team encounters challenges such as an overfitting problem and dataset bias. Despite achieving a 55-58% validation accuracy, they conclude that the lack of regularisation and data standardisation, along with the bias in the dataset, are possible reasons for the model's poor performance. In summary, the study highlights the potential of CNNs in emotion recognition but also underscores the need to address key challenges in the field. [1]

The paper "Facial emotion recognition using convolutional neural networks" proposes an approach called FERC that uses a two-part CNN to detect emotions. The first part removes the background from the image, while the second part focuses on extracting the face's feature vector. The FERC model employs an expressional vector (EV) to identify the five main regular facial expressions, achieving a 96% accuracy rate with an EV length of 24 values. By using a revolutionary background removal technique, FERC overcomes various potential issues, such as distance from the camera. The authors anticipate that FERC will be useful in several applications, including student predictive learning and lying detectors. However, one of the drawbacks of this approach is that it may not capture all 24 characteristics in the EV vector due to face orientation or shadows. The authors are attempting to address these issues by automatically correcting the gamma of photos and assuming facial symmetry. Overall, FERC presents a promising approach to emotion detection using CNNs, with potential for use in a range of practical applications. [2].

In the paper "Facial Emotion Recognition Using Deep Learning, Review, and Insights" presents a comprehensive study of the latest developments in automatic facial emotion recognition (FER) using deep learning. The authors explore the various steps involved in the FER process, including data processing, model architecture design, and emotion recognition. The authors discuss the various CNN and CNNLSTM architectures proposed by researchers and present a range of databases that include spontaneous images from real-world scenarios as well as laboratory-generated images. They highlight the significance of accurate emotion detection, which requires the use of large databases and powerful deep learning models. FER plays a crucial role in providing insights into human emotions and has advanced from unimodal to multimodal analysis. According to Pantic and Rothkrantz, multimodality is essential for the more accurate detection of human emotions. Therefore, researchers are now focusing on developing powerful multimodal deep learning architectures and databases to expand the scope of emotion recognition beyond the six basic emotions and neutral. The authors' conclusion underscores the potential of machines to interpret human emotions, making human-machine interactions increasingly natural. This, in turn, drives researchers to create larger databases and more sophisticated deep-learning models that can recognize a wider range of emotions. [3]

In this paper, "Study of a Machine Learning Model for Face Detection, Age Detection, and Gender Recognition", the authors investigate the use of machine learning methods and Python tools for face detection, age detection, and gender recognition. They use convolutional neural networks, rectified linear unit layers, and pooling layers to estimate age and gender, which allows for more accurate predictions. Additionally, their model can handle both image and webcam input, which makes it more user-friendly. CNN-based face recognition systems have become the industry standard due to their high accuracy, scalability, and ability to replace traditional hand engineered methods. However, training and deploying highly deep CNN architectures can be time-consuming and expensive. [13] The authors propose using generative adversarial networks (GANs) to solve the issue of large-scale face image labeling and more effective architectures for real-time face recognition on devices with constrained processing resources, such as MobileNets. Overall, this paper demonstrates the potential of machine learning and deep learning techniques in face detection, age detection, and gender recognition, and highlights the ongoing efforts to improve their accuracy and efficiency. [4]

The paper "Real-Time Emotion, Gender, Age Detection Using CNN" presents a CNN-based modelling architecture for real-time age, gender, and emotion detection from webcam facial photographs. The identification of these attributes is crucial for various applications. The paper discusses several approaches and tools, including SVM, LBP, HOG, PCA, and the Viola-Jones algorithm, that can be directly or indirectly used for this purpose. SVM is employed in regression and classification, LBP is used for texture categorization, HOG is a commonly used feature descriptor, PCA is utilized for high dimensional data with a linear model variation, and the ViolaJones algorithm is an object identification tool that can detect different item classes and faces in real-time applications. These techniques can help in accurately determining age, gender, and various human emotions from webcam facial photographs. In conclusion, the CNN-based modelling architecture described in the paper is an effective approach for real-time age, gender, and emotion detection. The use of these tools and techniques can lead to accurate identification of these attributes, which is essential for a wide range of applications. [5]

The paper "Emotion Recognition Using Convolutional Neural Network" explores the potential of Convolutional Neural Networks (CNNs) in recognizing human emotions through facial expressions. The emotional state of a person can be greatly influenced by their physical and mental health, and it is a key aspect of interpersonal communication. Despite being able to express emotions verbally through facial expressions, it can be challenging to accurately identify them due to the similarity of many patterns. The paper focuses on the development of an application for automatic emotion recognition, using real-time photographs as input. A CNN is applied to recognize emotions, with the identified emotion being displayed if successful. The created application achieved an average accuracy of 92.50 out of 100, with a sensitivity of 85.00 and a specificity of 95.00. The authors evaluated the CNN using a confused expression, which represents a common and important expression in everyday life [6]

In the paper "A Review on Finding Efficient Approach to Detect Customer Emotion Analysis using Deep Learning Analysis" delves into the various deep learning algorithms and the quest to find the most efficient approach for customer emotion analysis. The authors review various common deep learning algorithms for emotion recognition and utilize the eXnet library to improve accuracy. However, they acknowledge the challenges posed by memory and computation limitations and the risk of overfitting with large models. To address this, they employ a novel Convolutional Neural Network (CNN) named eXnet, which features parallel feature extraction and reduces overfitting while maintaining overall size. The most recent eXnet (Expression Net) model improves accuracy and has fewer parameters compared to previous models. The authors also incorporate data augmentation techniques to enhance the eXnet's performance, and the quantization method to improve its effectiveness in real-world scenarios. Despite its importance, this paradigm has some limitations, particularly when it comes to processing small datasets using CPUs. The authors suggest that using GPUs would be a more effective solution as the number of users increases [7].

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The paper ”Facial Emotion Recognition and Detection Using CNN” explores a method of identifying human emotions through facial expressions using a standard Convolutional Neural Network (CNN) and data augmentation. The authors aim to develop a system that can accurately categorize emotions, such as anger, disgust, fear, happiness, sadness, surprise, and neutral, through facial recognition. The authors suggest utilizing a CNN architecture for this task, as it is known to be effective in image classification applications, with its numerous filters. To train the network, they use the publicly available FER2013 dataset, which is considered large enough to train deep networks. [12] The proposed system consists of five modules: face capture, pre-processing, training, face recognition, and face expression recognition. The first module involves capturing images of faces using a webcam or external camera. The pre-processing module then converts the color images to grayscale for further processing. In the training module, the images are then organized into a dataset and saved in a .YML file for faster processing. The face recognition module uses the Local Binary Pattern (LBP) algorithm to identify faces in the database based on the previously saved face ID and name. Finally, the face expression recognition module uses biometric data to analyze the emotions present in the faces, providing an impartial and accurate representation of emotions. The authors highlight the benefits of their approach, including higher accuracy, improved computational efficiency, better image quality, and the ability to recognize emotions even in low-resolution photos.. [8]

In the paper “Customer Satisfaction Recognition through Emotions,” the authors propose a novel approach to detecting customer feedback by analyzing their emotions. The model employs a combination of Convolutional Neural Networks (CNN) and Haar Cascade Classifier to detect facial expressions, age, and gender of customers [11]. The model is trained using a dataset of pixelated images of individuals exhibiting different emotions. The process is divided into four phases: selection of the best Haar features, creation of integral images, training of the AdaBoost algorithm on the input image dataset, and using the cascading classifier to differentiate between pictures with and without faces. To further refine the data, the authors apply smoothing techniques such as grayscale conversion and noise reduction. The subtraction operation is used to distinguish between the background and foreground, and a threshold is applied to the resulting image to retain only pixels that are higher than the threshold. The proposed model is a real-time system that can detect faces in a live video feed and determine the emotion, allowing the authors to determine whether the customer is happy or not. The system is capable of identifying six emotions with an accuracy of approximately 89%One of the key advantages of the proposed approach is its˙ ability to classify the six emotions into three customer satisfaction levels: Satisfactory for Happy and Surprised, Completely Not Satisfactory for Sad, Angry, and Disgusted, and Neutral for the Neutral class. [9].

The paper titled ”Facial Emotion Recognition Analysis Based on Age-Biased Data” delves into the significance of considering age as a crucial factor in the recognition of emotions through facial expressions. To accomplish this, a bespoke dataset was created, comprising of images of adults and children, that were segregated from existing datasets like FER2013 and MMA FACILE EXPRESSION. The study employed Convolutional Neural Networks (CNN) to evaluate the accuracy of emotion recognition. Three distinct CNN architectures - MobileNet-V2, SE-ResNeXt50 (32 × 4 d), and ResNeXt-101 (64 × 4 d) - were experimented with, and the highest accuracy was achieved by SE-ResNeXt50 (32 × 4 d) with an accuracy rate of 79.42%The model trained with age-˙ biased data displayed a 22.24% accuracy rate compared to the model that did not consider age as a factor. The results of the study indicated that the greatest difference in expressions was observed between adults and children for the emotions of fear and neutrality. This research provides valuable insights and comparative data to researchers in the field of emotion recognition and sheds light on the age bias issue that affects emotion recognition models. [10]

IV. RESEARCH ISSUE AND FUTURE SCOPE

In this section, we primarily discuss the research gaps that need to be filled. According to all prior studies, no researcher has ever addressed the following most crucial and vital issues:

- ➢ All of the approaches we’ve discussed are constrained by our understanding of just the six fundamental emotions plus neutral. It clashes with more nuanced emotions seen in daily life.
- ➢ Age and gender have an impact on how emotions are expressed, and this also applies to customer feedback, which hasn’t been well addressed.
- ➢ Human emotions can occasionally be misled since there may be other factors at play. Similar to how not all customers may express themselves as well as others. In these circumstances, the information we gather from their emotions would no longer be reliable.
- ➢ To acquire precise results, we must train CNN using a huge dataset. However, it will take a long time to do this.

- *Future Objectives:*

Future goals include resolving any issues that have arisen in the past and developing a system that is balanced and produces high-quality results across the spectrum.

- ✓ We require a system that can recognize even ambiguous emotions.
- ✓ For more effective understanding, the system should be able to analyze customer feedback from each age group and gender differences.
- ✓ When evaluating customer satisfaction from feed, we need to be able to take the frequency of customers’ visits into account in order to avoid being misled by consumers’ fake emotions or emotionless expressions.

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- ✓ We need a system that can be trained with modest datasets and produce reliable results.

V. CONCLUSION

The field of emotion recognition has immense potential for transforming human-machine interaction by enabling machines to detect and respond to human emotions. Deep learning techniques, particularly convolutional neural networks, have emerged as a popular method for combining feature extraction and classification. However, challenges such as dataset bias, overfitting, and large-scale image labeling hinder the accuracy and efficiency of these models. Despite these obstacles, the promise of deep learning models in emotion recognition remains unwavering, and researchers are exploring innovative solutions to overcome these challenges. The potential applications of human emotion analysis span across a multitude of industries, including healthcare, advertising, and gaming. Customer satisfaction is a crucial aspect of the business world, and the ability to recognize customer emotions can prove immensely beneficial in enhancing overall customer experience. However, emotion analysis is a challenging task that requires a variety of input modalities. This paper presents a comprehensive analysis of existing approaches and relevant research to construct an effective Age Separated Customer Feedback System based on Emotion Detection, identifying various potential opportunities in this area. The ability to understand emotions is critical to building more intuitive and responsive machines that can enhance our daily lives.

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