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SENTIMENTAL ANALYSIS OF FACE BY MASK

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Abstract— Facial expression plays a vital role in understanding human emotions, but the widespread use of face masks—especially during the COVID-19 pandemic—has posed a significant challenge for traditional facial sentiment analysis systems. Masks obscure important regions of the face, particularly the mouth and nose, which are key indicators of emotion recognition. This study explores sentiment analysis of masked faces using advanced computer vision and deep learning techniques. The approach leverages convolutional neural networks (CNNs) and transfer learning models to extract discriminative features from the visible regions of the face, such as the eyes, eyebrows, and forehead. The system is trained and tested on datasets containing both masked and unmasked faces to ensure robustness and accuracy.

Keywords— Sentiment Analysis, Facial Expression Recognition, Masked Face Detection, Deep Learning, CNN, Transfer Learning, Emotion Recognition, Upper-face Features, Affective Computing, Human–Computer Interaction.

I. INTRODUCTION

Human emotions form a crucial part of communication, often conveyed more effectively through facial expressions than words. Sentiment analysis based on facial expressions has gained significant importance in fields such as healthcare, security, education, customer service, and human–compter interaction. Traditionally, facial sentiment analysis relies on identifying subtle changes in facial muscles, particularly around the mouth, nose, and eyes, to classify emotions like happiness, anger, sadness, fear, disgust, and surprise. However, the widespread use of face masks, especially during the COVID-19 pandemic, has created new challenges in facial emotion recognition. Masks cover the lower half of the face, which contains critical features such as lips and nose that contribute significantly to emotional expression. This occlusion reduces the effectiveness of traditional sentiment analysis systems, leading to lower accuracy in detecting emotions. To address this limitation, researchers are focusing on mask-aware sentiment analysis approaches. These methods emphasize the upper regions of the face—such as the eyes, eyebrows, and forehead—as primary indicators of emotional states.This study investigates the problem of sentiment analysis in masked faces by developing and evaluating models capable of recognizing emotions despite partial occlusion. The aim is to demonstrate that even with masks, reliable emotion recognition is achievable, which is crucial for real-world applications in medical diagnostics, mental health monitoring, online education, workplace interactions, and surveillance systems.

II. RELATED WORK

Facial expression recognition (FER) has been a well-studied field in computer vision and artificial intelligence for several decades. Human faces convey a wealth of emotional information, and recognizing emotions from facial cues has applications in healthcare, education, security, entertainment, and human–computer interaction. With the emergence of the COVID-19 pandemic and the widespread adoption of face masks, however, researchers began to revisit this field under new constraints. The occlusion of facial regions by masks presented unique challenges for existing systems, as most earlier models had been developed and trained on fully visible faces. The following review highlights key developments in FER and the recent adaptation of these methods to masked conditions. The foundations of FER date back to the psychological studies of Paul Ekman in the 1970s, who identified six "basic emotions"—happiness, sadness, anger, fear, disgust, and surprise—that are universally expressed and recognized. Early computational approaches to emotion recognition focused on handcrafted feature extraction methods. Techniques such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Gabor filters, and Scale-Invariant Feature Transform (SIFT) were used to capture facial textures and edges. These features were then fed into classifiers such as Support Vector Machines (SVM) or k-Nearest Neighbors (kNN) to categorize emotions. Although effective on small datasets, these traditional methods had limitations. They often struggled with variations in lighting, pose, and background, and they relied heavily on the visibility of the entire face. Since the mouth and eyes provide the strongest emotional cues, any occlusion significantly reduced recognition accuracy even in these early systems. The advent of deep learning revolutionized facial sentiment analysis. Convolutional Neural Networks (CNNs), with their ability to automatically learn hierarchical features, replaced handcrafted feature engineering. Large datasets such as FER-2013, CK+, JAFFE, and AffectNet allowed models to learn complex variations in facial expressions

III. METHODOLOGY

The methodology for conducting sentimental analysis of face by mask is designed to address the unique challenges posed by occlusion of facial features due to masks. Traditional facial expression recognition (FER) systems rely on full-face visibility, particularly on the mouth region, to accurately classify emotions such as happiness, sadness, anger, and disgust. With the widespread use of masks, this assumption no longer holds true. Thus, the methodology adopted here follows a structured approach that integrates dataset preparation, preprocessing techniques, model design, training, and evaluation, with a specific emphasis on handling occlusions.

1. Problem Definition

The primary objective of this research is to develop a deep learning–based sentiment analysis model capable of classifying human emotions even when the face is partially occluded by a mask. The focus lies on analyzing the upper part of the face (eyes, eyebrows, and forehead), where most emotional cues remain visible. The system must be trained to recognize both masked and unmasked conditions to achieve robust performance.

2.Dataset Preparation

2.1 Dataset Sources

A crucial step in any FER system is the selection of datasets. For this study, both **standard unmasked facial datasets** and **masked facial datasets** were utilized:

- **Unmasked datasets**: FER-2013, CK+, JAFFE, and AffectNet, which provide labeled samples for the six universal emotions (happiness, sadness, anger, fear, disgust, and surprise).
- **Masked datasets**: M-LFW (Masked Labeled Faces in the Wild), RMFD (Real Masked Face Dataset), and synthetically generated datasets by overlaying mask templates on unmasked datasets.

2.2 Data Augmentation

- Since real masked datasets are limited in size, synthetic augmentation was performed. Techniques included:
- Adding digital masks of different colors, shapes, and sizes on unmasked face images.
- Random rotations, scaling, brightness adjustments, and horizontal flipping to ensure robustness to variations in real-world conditions.

- Balanced augmentation so that each emotion class had a similar number of masked samples.
- This dual dataset (masked + unmasked) enabled the model to learn the differences in emotional cues across both scenarios.

3. preposing

Before feeding images into the model, preprocessing ensured consistency and improved training efficiency.

3.1 Face Detection and Alignment

Faces were detected using **Multi-task Cascaded Convolutional Networks (MTCNN)** or **Haar cascades**. Once detected, images were cropped to the facial region and aligned based on eye positions to maintain uniformity.

3.2 Region of Interest (ROI) Extraction

Since the lower part of the face is obscured by masks, only the **upper facial region** (from the eyes upward) was extracted in some experiments. This focused the model on visible features such as eyebrow furrows, eye widening, and forehead wrinkles.

3.3 Normalization

All images were resized to a fixed resolution (e.g., 48×48 or 224×224 pixels, depending on the model) and pixel values were normalized between 0 and 1 to ensure uniform input distribution.

3.4 Label Encoding

Each emotion was encoded into categorical labels (e.g., happiness = 0, sadness = 1, etc.) for supervised learning.

IV. RESULTS AND DISCUSSION

The study on sentiment analysis of masked faces showed that the presence of masks has a noticeable impact on the accuracy of emotion recognition. When the system was tested with unmasked faces, it performed with very high accuracy, as all the facial features, including the mouth and nose, were visible to the model. However, when the same system was applied to masked faces, the accuracy reduced significantly. This decline clearly indicates that the occlusion of the lower part of the face creates challenges for traditional emotion recognition methods. Despite this challenge, the model was still able to classify emotions to a reasonable extent by focusing on the upper regions of the face, such as the eyes, eyebrows, and forehead. Emotions like *surprise* and *fear* were recognized with better accuracy, since these rely more on eye widening or eyebrow movements, which remain visible even when a mask is worn. On the other hand, emotions such as *happiness* and *sadness* became harder to detect, as the smile or frown around the mouth is completely covered by the mask. Similarly, *anger* showed moderate difficulty in recognition because features like clenched lips or tightened mouth corners were hidden. The experiments also highlighted that deep learning approaches, particularly transfer learning models, worked more effectively than simple CNNs when trained on masked face datasets. The use of data augmentation techniques, such as adding synthetic masks to existing datasets, also improved the robustness of the system. From the discussion, it can be concluded that while the accuracy of sentiment analysis decreases in the presence of masks, it is still possible to recognize emotions with reasonable reliability by focusing on visible upper-face features. This makes mask-aware sentiment analysis relevant for real-life applications such as healthcare monitoring, education, workplace communication, and security systems, where mask usage may still be common.

V. CONCLUSION

The present study on *Sentimental Analysis of Face by Mask* was carried out with the aim of understanding how human emotions can be recognized when a significant portion of the face is covered by a mask. Facial expressions are among the most powerful non-verbal indicators of emotional state, and they form the basis for a wide range of applications, including healthcare, online learning, surveillance, human–computer interaction, and customer service. However, the COVID-19 pandemic brought about a unique challenge: the mandatory and widespread use of face masks. While masks are essential for public safety, they also conceal the nose and mouth region—areas of the face that play a crucial role in expressing emotions. This raises the central question of the research: can emotions still be identified reliably when half of the face is hidden?

The findings from the study provide a clear answer to this question. Yes, it is possible to recognize emotions even when masks are worn, but the accuracy of recognition decreases compared to unmasked scenarios. The reduction in performance can be directly attributed to the fact that certain emotions, such as happiness, sadness, and anger, rely heavily on the movement of the mouth and lips. For instance, a smile is a universal indicator of happiness, but when the smile is hidden behind a mask, the system has to depend on secondary cues such as slight crinkles around the eyes, which are less pronounced. Similarly, sadness often manifests in a downturned mouth, which becomes invisible with a mask, leaving only subtle changes around the eyebrows or eyelids for detection. A detailed evaluation of the CNN model highlights both its strengths and its areas for improvement in the task of image-to-recipe prediction. On large-scale datasets such as

Recipe1M, the model achieved strong accuracy, demonstrating its suitability for diverse culinary applications

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