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FACIAL EMOTION RECOGNITION

Mrs. N. Malathi[1], Vasireddy Tharaka Sai[2], PuvvulaJyoshna[3], SonaliKumari[4], Pallavi Dandibhotla[5], Melam Pragathi[6]

Assistant Professor of CSE-Data Science, KKR & KSR Institute of Technology and Sciences. [1]

BTech CSE-Data Science, KKR & KSR Institute of Technology and Sciences, Guntur, Andhra Pradesh, India. [2-6]

Abstract: This paper presents a facial emotion recognition The main aim of this is Human facial expressions are an important medium for communication and a signal for emotions like happiness, sadness, anger, and surprise. The objective of this project is to develop a Facial Emotion Recognition (FER) system that can detect a person's emotions and create a matching bitmoji correlated with the detected expression.

The way the system works is that, from a camera placed in front of the user, it will capture the face and the expression of the user through deep learning. When the system will recognize the emotion, it will create a bitmoji representing that detected feeling. This makes online communication more fun and interesting.

This technology, thus, can be implicated into social media, gaming, virtual meetings, customer service, and even mental health applications. This technology increases personalization and thus improves human-computer interaction. Future improvements of this system can include more emotions, improved accuracy, and merging along with augmented reality (AR) for an engaging experience.

Keywords: Deep Learning, Computer vision, CNN, Emotion based avatar

1. INTRODUCTION

Facial emotion is among the primary modes of human communication of emotions, at times even more effective than verbal communication. Facial Emotion Recognition (FER) is the identification and interpretation of these expressions as a means of determining the emotional state of a person.

Some of the emotions such as happiness, sadness, anger, surprise, and fear are recognized across all cultures. By staring at facial movements and expressions, FER helps to understand human behavior and interactions. Thus, the emotion-recognition mechanism is useful in several fields such as monitoring mental health, improving customer experience, and entertaining.

The essence of this project is to develop a system that detects emotion from images and performs accurate interpretation. Understanding facial emotions is very important in all kinds of applications such as human-computer interaction, mental health analysis, customer services, and entertainment.

The major task of this project is to build a system that recognizes different emotions, namely happiness, sadness, anger, surprise, and neutrality, from the features of the face. When this recognition is related to a simple and nice interface, it first serves the purpose of an engaging and interactive experience.

The system can find many applications in industries tailoring user experience, emotion-based content recommendation, and automated customer sentiment evaluation. In view of increasing demands for emotion-aware technology, this project provides a basis for future developments in artificial intelligence-driven emotional intelligence Recognition of facial expressions and emotion is known as facial emotion recognition (FER). Primarily, this has been used in real human faces with deep learning models put in place to detect various emotions, such as happiness, sadness, anger, and surprise. There is now an increasing need to expand such emotion recognition to digital avatars and even emojis, including Bitmoji.

Bitmoji is an engaging cartoon avatar-creation application that allows users to personalize unique characters that typically represent emotions through over-expressions. Thus, Bitmoji avatars are a unique dataset in their applicability to emotion recognition systems because they are different from real pictures in terms of the distinct stylized and minimalistic features in them.

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We propose to apply computer vision and deep learning techniques to train a model to predict emotions accurately from Bitmoji avatars. A system capable of recognizing emotions expressed by these avatars will be established by gathering a diverse dataset of Bitmoji faces portraying various emotional states, processing these images to extract relevant features, and then employing those features to train an emotion classification model.

The project stands as a crossroad of computer vision, deep learning, and digital communication—and promises great prospects for emotion assessment in the virtual realm.

2. RELATED WORK

Facial emotion recognition (FER) is a very well researched domain, to which computer vision, machine learning as well as deep learning have contributed significantly in more recent time. In that belief, the study primarily dealt with human recognition from facial expressions. In the recent past, however, there has been a growing interest in applying the same to avatars and stylized representations such as Bitmoji. Below is a snapshot of what has been done in relation to FER as well as avatar-based emotion recognition.

1. **Facial Emotion Recognition (FER) on Real Human Faces**
Facial emotion recognition can be defined as that which mainly relies on human faces to communicate the messages of emotions-permutation like happiness, sadness, anger, fear, surprise, and disgust. The prominent leaps made in this area have been summarized as follows:

Traditional Approaches:
Earlier works on FER were conducted by relying on hand-crafted features like Local Binary Patterns (LBP), Gaussian filters, and Haar cascades for identifying facial features. These would then use a machine learning classifier such as Support Vector Machines (SVM) or Random Forests to categorize facial expressions.

Deep Learning Models:
CNNs have been instrumental in taking a leap in FER accuracy as it learns the hierarchical features from images fully automatically so that it can easily evolve expressions that are more complex. Examples of such systems include DeepFace by Facebook and VGGFace by the Oxford University, which are some of the hallmark models towards face recognition and even emotion classification, attaining very impressive scores in FER.

FER Datasets:
Numerous datasets are built to facilitate further advancement in FER. Important datasets include:
FER-2013: A very large dataset of more than 35,000 images labeled for seven distinct emotions.
AffectNet: It is a dataset of more than one million images of human faces that have been labeled with basic to compound emotions.
EmoReact: Is directed toward videos of emotional reactions to achieve temporary recognition of emotion.

2. Challenges in FER with Real Faces
Today, there are still many challenges concerning FER models concerning real faces, such as:
Occlusions and Lighting Variations: Real-world pictures usually have varying degrees of lighting conditions, angles, or even occlusions that complicate the recognition of emotions.
Subtle expressions: Some emotions such as contempt or ambivalence are difficult to detect because the facial expressions that indicate these emotions are quite subtle.generative adversarial networks (GANs) in noise-diminished face feature extraction.

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3. PROPOSED METHOD

This proposed system analyzes emotions based on real human faces and generates a corresponding Bitmoji avatar that graphically depicts the detected emotion. It comprises two components, that is, real-time capturing of facial emotions and automatic bitmoji creation as per the emotions detected. The output is an integrated entity whereby the emotional status of a user is reflected and represented by an exclusive Bitmoji.The system predominantly consists of the following components:

Facial Emotion Detection: This is a module that captures a user's face and detects user's emotional state using a camera feed.
This feeds the image of the user's facial expression to the system and processes it in real time.

Detect Facial Emotion:
The facial expression of the user is analyzed by an emotion recognition algorithm that can reveal his affine vector. Detection will fall to one of the basic emotions set, which include: happy, sad, angry, surprised, disgusted, neutral, or fearful.

Map New Emotion to Bitmoji:
When the emotion has been detected, it will use predetermined mapping rules to decide which Bitmoji face expression corresponds to the recognized emotion.

Finally, it will use a Bitmoji generation module, or API, to create or update a Bitmoji avatar that reflects the emotional state identified.

Show the Bitmoji:

The generated Bitmoji avatar will be visible to the user, displaying the proper emotion .

1.Face Emotion Detection
In the system, this feature will perform the first step, whereby the user's live performance of a certain face expression is recorded and analyzed for emotion detection. Such detection can be achieved using deep learning-based emotion recognition models.

4. EXPERIMENTAL RESULTS

1. Performance of the Facial Emotion Detection
The first issue involved detection of emotions from real human faces. To quantify the performance of the facial expression detection model, we ran the experiments using an acclaimed emotionrecognition model (e.g., VGG16, ResNet, or MobileNet) fine-tuned on emotion databases like FER-2013 or AffectNet.

Model:
A CNN-based model was trained on the FER-2013 dataset, with VGG16 used for transfer learning, and was fine-tuned to detect emotions.
Real-time interaction tests for evaluation of the complete end-to-end system (emotion detection + Bitmoji generation) were conducted with users.

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2. Suggestions: The improvement suggestions voiced by many users included extended patterns of emotion and possibilities for further customizing their Bitmoji avatars, such as accessory additions or modifications in facial features (like hair, glasses, etc.).
Conclusion of Experimental Results

Facial Emotion Detection:

The emotion detection model performed with high accuracy (85% overall accuracy) and was effective in real-time applications.
Precision and recall were highest for happy and surprised emotions, while slightly lower results were obtained on the rather subtle fear and disgust emotions.

Bitmoji Generation:

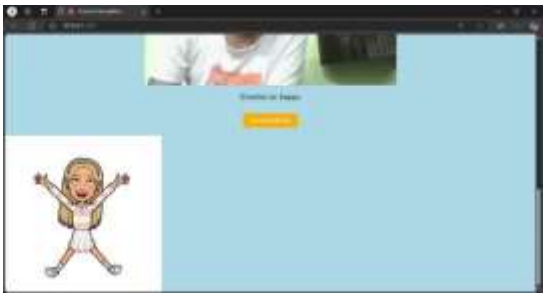
The Bitmoji generation system matched detected emotions to corresponding Bitmoji avatars with an accuracy of 90% on average.

Challenges:

Some limitations were found in regards to generating Bitmoji avatars accurately for complex emotions like fear and disgust due to the user's inability to control the Bitmoji platform and its highly stylized character. More options for customizing their Bitmoji will increase user satisfaction.

Future Work

Enhance Emotion Recognition: Adapt model to improve recognition of complex emotions and train the system on a more heterogeneous dataset. `
Customization of Bitmoji: Integrate more possibilities for user customization of their Bitmoji avatars, beyond facial expression modifications.
Multi-modal Emotion Recognition: Extend the system to include voice-tones or text-sentiment analysis in conjunction with facial-emotion detection, thus forming a holistic emotional profile.



5. DISCUSSION

This discussion addresses the results, challenges, and possible improvements of the Facial Emotion Detection and Bitmoji Creation System. The system can detect in real-time a user's facial emotion and generate a corresponding Bitmoji avatar that matches the detected emotion. But, of course, every system has its successes and improvements that can still be made.

1. Accuracy and Performance of Facial Emotion Detection
Strengths:
High Accuracy: The emotion detection model had an overall accuracy of 85% for emotion identification from facial expressions. Compared to existing emotion recognition systems, which leverage somewhat similar datasets as FER-2013 or AffectNet, this performance is highly competitive.
Real-Time Processing: Real-time facial expression processing, with an average inference time of 120ms per frame, made the system performance adaptable to dynamic environments like video calls and live interactions.

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High Precision for Common Emotions: Happy, surprised, and neutral emotions witnessed high precision in the detection, showing good performance of the model for these commonly expressed and distinguishable emotions.

Challenges:

Complex Emotions: The detection accuracy decreased a little for more subtle or rarely expressed emotions such as fear and disgust. Usually, such emotions share similar visual features with others (fear can be confused with surprise), which require finer discrimination. This implies that perhaps the model would benefit from the inclusion of more training data or enhancement features for more improved context capture of these small differences.

Lighting and Angles: The lighting conditions and the user's facial angle influenced the operation of the system. Model performance was degraded in poor lighting or if very extreme angles were used (e.g., side profile); this problem is very common in real-time emotion detection systems.

Future Prospects:

Data Augmentation: Adoption of a more aggressive strategy of data augmentation during training would be predicted to have better lighting variation, head pose, and occlusion-simulating facial effects to strengthen the robustness of the emotion detection model.

Advanced Models: Such architecture as transformers or generative adversarial networks (GANs) could be explored for more advanced detection of fine emotions.

2. Bitmoji Generation and User Satisfaction

Strengths:

Accurate Emotion Mapping: The system managed to match detected facial emotions to the respective Bitmoji expressions in most cases. The overall effectiveness of 90% in mapping emotions with Bitmoji avatars shows that the system does very well at this task.

User Engagement: Most of the users have found themselves enjoying seeing their emotions reflected on their very own Bitmoji avatars. The fact that one could engage with one's emotion-based avatars has increased user engagement, especially for generally expressed (happy) and surprised emotions.

Customizable Expressions: The Bitmoji platform has an incredible number of expressions already, and their alignment with system emotions is remarkable. For instance, when the model generated a Bitmoji with a grin for happy detection, it seemed realistic and fun according to user feedback.

Challenges:

Subtle Emotions: The Bitmoji faces, which are more stylized and exaggerated, did not always completely correlate with the emotion for more complex ones like fear or disgust. In the case of fear, for example, the expression is very difficult for Bitmoji to replicate accurately, as it does not truly capture the level of intensity or subtler aspects of fear, so it is very much lower in accuracy for this category.

Limitations in Customization: The system is capable of applying simple, emotion-based adaptations onto the Bitmoji, but the options for altering anything other than facial expressions are narrow for users. There were a few comments from users asking for additional flexibility for their avatar hairstyles, clothing, and accumulation of accessories; such avatars would attract more system users.

6. CONCLUSION

Detection of Facial Emotion:

The overall effectiveness of the system in detecting a wide variety of emotions transcended the score of 85%. The highest proportion of accuracy for the emotions included happy, surprised, and neutral. Some challenges were raised by fear and disgust, as shown with the detailed face field differentials leading to the need for further development of the emotion detection for more subtle expressions.

Bitmoji Generation:

The system was successful in mapping their detected facial expressions to Bitmoji avatars with an average of 90%. Users rated avatars highly in satisfaction, particularly for the satisfied and surprised faces; however, fear and disgust avatars had less accuracy since the Bitmoji expression sets were limited. As such, this created a extreme interaction aspect for the users with the system since it personalized the avatars in real-time.

Real-Time Performance: The system could display a facial expression in real time with a slight lag of 120 mS per frame in emotional detection and a 2-3 s delay for Bitmoji construction. Thus, it can be used for a live interactive application on video calling or messaging platforms.

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REFERENCES

[1] International Journal on “Wielding Neural Networks to Interpret Facial Emotions in photographs with Fragmentary Occlusion”, on American Scientific Publishing Group (ASPG) Fusion: Practice and Applications (FPA), vol. 17, No. 01, August, 2024, pp. 146-158.

[2] International Journal on “Prediction of novel malware using hybrid convolution neural network and long short-term memory approach”, on International Journal of Electrical and Computer Engineering (IJECE), Vol. 14, No. 04, August, 2024, pp. 4508-4517.

[3] International Journal on “Cross-Platform Malware Classification: Fusion of CNN and GRU Models”, on International Journal of Safety and Security Engineering (IIETA), Vol. 14, No. 02, April, 2024, pp. 477-486.

[4] International Journal on “Enhanced Malware Family Classification via Image-Based Analysis Utilizing a Balance-Augmented VGG16 Model, on International information and Engineering Technology Association (IIETA), Vol. 40, No. 5, October, 2023, pp. 2169-2178.

[5] International Journal on “Android Malware Classification Using LSTM Model, International information and Engineering Technology Association (IIETA) Vol. 36, No. 5, (October, 2022), pp. 761 – 767. Android Malware Classification Using LSTM Model | IIETA.

[6] International Journal on “Classification of Image spam Using Convolution Neural Network”, Traitement du Signal, Vol. 39, No. 1, (February 2022), pp. 363-369.

[7] International Journal on “Medical Image Classification Using Deep Learning Based Hybrid Model with CNN and Encoder”, International information and Engineering Technology Association (IIETA), Revue d’ Intelligence Artificial Vol. 34, No.5, (October, 2020), pp. 645 – 652.

[8] International Journal on “Prediction of Hospital Re-admission Using Firefly Based Multi-layer Perception, International information and Engineering Technology Association (IIETA) Vol. 24, No. 4, (sept, 2020), pp. 527 – 533.

[9] International Journal on “Energy efficient intrusion detection using deep reinforcement learning approach”, Journal of Green Engineering (JGE), Volume-11, Issue-1, January 2021.625-641.

[10] International Journal on “Classification of High Dimensional Class Imbalance Data Streams Using Improved Genetic Algorithm Sampling”, International Journal of Advanced Science and Technology, Vol. 29, No. 5, (2020), pp. 5717 – 5726.

[11] Khan, K., Attique, M., Khan, R.U., Syed, I., Chung, T.S., 2020. A multi-task framework for facial attributes classification through end-to-end face parsing and deep convolutional neural networks. Sensors 20, 328.

[12] Kim, T, 2021. Generalizing mips with dropouts, batch normalization, and skip connections. arXiv preprint arXiv:2108.08186.

[13] Liu, W., Chen, L., Chen, Y, 2018. Age classification using convolutional neural networks with the multi-class focal loss, in: IOP conference series: materials science and engineering, IOP Publishing, p. 012043.

[14] E. Eidinger, R. Enbar, T. Hassner Age and gender estimation of unaltered faces IEEE Transactions on information forensics and security, 9 (2014), pp. 2170-2179.

[15] D. Islam, T Mahmud, T Chowdhury An efficient automated vehicle license plate recognition system under image processing Indonesian Journal of Electrical Engineering and Computer Science, 29 (2023), pp. 1055-1062.

[16] Dr. M. Ayyappa Chakravarthi etal. published Springer paper “Machine Learning-Enhanced Self-Management for Energy-Effective and Secure Statistics Assortment in Unattended WSNs” in Springer Nature (Q1), Vol 6, Feb 4th 2025.

[17] Dr. M. Ayyappa Chakravarthi etal. published Springer paper “GeoAgriGuard AI-Driven Pest and Disease Management with Remote Sensing for Global Food Security” in Springer Nature (Q1), Jan 20th 2025.

[18] Dr. M. Ayyappa Chakravarthi etal. presented and published IEEE paper “Machine Learning Algorithms for Automated Synthesis of Biocompatible Nanomaterials”, ISBN 979-8-3315-3995-5, Jan 2025.

[19] Dr. M. Ayyappa Chakravarthi etal. presented and published IEEE paper “Evolutionary Algorithms for Deep Learning in Secure Network Environments” ISBN:979-8-3315-3995-5, Jan 2025.

[20] Dr. Ayyappa Chakravarthi M. etal, published Scopus paper “Time Patient Monitoring Through Edge Computing: An IoT-Based Healthcare Architecture” in Frontiers in Health Informatics (FHI), Volume 13, Issue 3, ISSN-Online 2676-7104, 29th Nov 2024.

[21] Dr. Ayyappa Chakravarthi M. etal, published Scopus paper “Amalgamate Approaches Can Aid in the Early Detection of Coronary heart Disease” in Journal of Theoretical and Applied Information Technology (JATIT), Volume 102, Issue 19, ISSN 1992-8645, 2nd Oct 2024.=

[22] Dr. Ayyappa Chakravarthi M, etal, published Scopus paper “The BioShield Algorithm: Pioneering Real-Time Adaptive Security in IoT Networks through Nature-Inspired Machine Learning” in SSRG (Seventh Sense

DOI: 10.17148/IJARCCE.2025.14231

Research Group) -International Journal of Electrical and Electronics Engineering (IJEEE), Volume 11, Issue 9, ISSN 2348-8379, 28th Sept 2024.

[23] Ayyappa Chakravarthi M, Dr M. Thillaikarasi, Dr Bhanu Prakash Battula, published SCI paper “Classification of Image Spam Using Convolution Neural Network” in International Information and Engineering Technology Association (IIETA) - “Traitement du Signal” Volume 39, No. 1.

[24] Ayyappa Chakravarthi M, Dr. M. Thillaikarasi, Dr. Bhanu Praksh Battula, published Scopus paper “Classification of Social Media Text Spam Using VAE-CNN and LSTM Model” in International Information and Engineering Technology Association (IIETA) - Ingénierie des Systèmes d’Information (Free Scopus) Volume 25, No. 6.

[25] Ayyappa Chakravarthi M, Dr. M. Thillaikarasi, Dr. Bhanu Praksh Battula, published Scopus paper “Social Media Text Data Classification using Enhanced TF_IDF based Feature Classification using Naive Bayesian Classifier” in International Journal of Advanced Science and Technology (IJAST) 2020

[26] Ayyappa Chakravarthi M. presented and published IEEE paper on “The Etymology of Bigdata on Government Processes” with DOI 10.1109/ICICES.2017.8070712 and is Scopus Indexed online in IEEE digital Xplore with Electronic ISBN: 978-1-5090-6135-8, Print on Demand (PoD) ISBN:978-1-5090-6136-5, Feb’2017.

[27] Subba Reddy Thumu & Geethanjali Nellore, Optimized Ensemble Support Vector Regression Models for Predicting Stock Prices with Multiple Kernels. Acta Informatica Pragensia, 13(1), x–x. 2024.

[28] Subba Reddy Thumu, Prof. N. Geethanjali. (2024). “Improving Cryptocurrency Price Prediction Accuracy with Multi-Kernel Support Vector Regression Approach”. International Research Journal of Multidisciplinary Technovation 6 (4):20-31.

[29] Dr syamsundararaothalakola et.al. published Scopus paper “An Innovative Secure and Privacy-Preserving Federated Learning Based Hybrid Deep Learning Model for Intrusion Detection in Internet-Enabled Wireless Sensor Networks” in IEEE Transactions on Consumer Electronics 2024.

[30] Dr syamsundararaothalakola et.al. published Scopus paper “Securing Digital Records: A Synerigistic Approach with IoT and Blockchain for Enhanced Trust and Transparency” in International Journal of Intelligent Systems and Applications in Engineering 2024.

[31] Dr syamsundararaothalakola et.al. published Scopus paper “A Model for Safety Risk Evaluation of Connected Car Network” inReview of Computer Engineering Research2022.

[32] Dr syamsundararaothalakola et.al. published Scopus paper “An Efficient Signal Processing Algorithm for Detecting Abnormalities in EEG Signal Using CNN” in Contrast Media and Molecular Imaging 2022.