RESEARCH ARTICLE OPEN ACCESS

# Micro Expression Detection Using Federated Learning

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## ABSTRACT

Annotation of large-scale facial expression datasets in the real world is a major challenge because of privacy concerns of the individuals due to which traditional supervised learning approaches won't scale. Moreover, training models on large curated datasets often leads to dataset bias which reduces generalizability for real world use. This work focuses on the development of a novel approach for micro-expression detection using federated learning. Micro-expressions are brief, involuntary facial expressions that reveal genuine emotions and intentions, often lasting for less than a second. Traditional methods for micro-expression analysis require centralized datasets, posing privacy and security concerns. Federated learning offers a decentralized and privacy-preserving solution by enabling model training on local devices without sharing sensitive data. In this work, we propose a federated learning framework for micro-expression detection that leverages the power of edge devices, such as smartphones and surveillance cameras, to capture and analyze facial expressions. We aim to develop a robust and efficient deep learning model that can be trained across these distributed devices while preserving the privacy of individuals. The key components of our approach include secure aggregation techniques, model optimization for resource-constrained devices, and a user-friendly application for real-time micro-expression analysis. We anticipate that our research will contribute to advancements in emotion recognition, security, and privacy protection. Furthermore, this project aligns with the growing demand for decentralized machine learning solutions in various domains.

## I. INTRODUCTION

The need for data privacy has increased the challenge of utilizing a central training approach for creating a machine learning model, which carries the risk of exposing confidential information and encroaching on the privacy rights of the data owner. The proposed work aims to introduce a novel technique in the rapidly evolving domain of facial expression analysis by employing federated learning techniques. This innovative architecture increases the precision of micro expression detection while protecting the privacy of sensitive face data by allowing the decentralised training of machine learning models on local devices. By combining the fields of emotion analysis and federated learning, this project seeks to usher in a new era of intelligent, privacy-preserving technology with applications ranging from human-computer interaction to emotion-aware computing. This research harnesses the potency of Convolutional Neural Networks (CNNs) within the paradigm of federated learning to achieve precise Micro Expression Detection. The CNN architecture facilitates feature extraction from facial micro expressions, capturing subtle nuances crucial for emotion recognition. Federated learning, employed here, distributes the model training across decentralized devices, ensuring that sensitive facial data remains on the local device, thus addressing privacy concerns. The CNN layers are tailored to discern intricate patterns in facial expressions, enabling the model to recognize and categorize micro expressions effectively. Federated learning orchestrates collaboration among these localized models, aggregating insights without centralizing the data. This synergistic fusion of CNN and federated learning not only enhances detection accuracy but also upholds privacy standards, making it a pioneering venture in the realm of emotion analysis and machine learning. The "Micro Expression Detection Using Federated Learning" project is situated at the intersection of facial expression analysis, deep learning, and privacy-centric artificial intelligence. The work is driven by the increasing importance of identifying micro expressions, or fleeting facial movements that convey subtle emotions, in the field of facial expression analysis. The study aims to raise the accuracy of emotion recognition by extracting delicate information from micro expressions and applying Convolutional Neural Networks (CNNs) to boost their strength. Federated learning was selected due to its ability to mitigate privacy issues related to centralised data processing. The goal of this work is to increase the accuracy of emotion identification while protecting the privacy of sensitive face data by distributing model training over several devices. In summary, the project amalgamates advancements in facial expression analysis, CNNs, and federated learning to pioneer a privacy-conscious approach to micro expression detection, contributing to the broader goal of developing emotionally intelligent artificial systems. Traditional centralized approaches to machine learning often raise privacy red flags, especially when dealing with sensitive facial data. In an era where human-computer interaction is becoming more nuanced, the ability to detect micro expressions offers a pathway to creating emotionally intelligent systems. Leveraging the power of Convolutional Neural Networks, our project aligns with the cutting-edge advancements in deep learning for facial expression analysis. Federated learning presents an opportunity to innovate the way machine learning models are trained.

## II. OBJECTIVE

To construct a Micro Expression Detection system with privacy preservation using Federated Learning, the project entails a sophisticated integration of facial expression analysis, deep learning, and decentralized model training. Commencing with the assembly of a diverse dataset encompassing micro expressions, the system focuses on preprocessing to extract nuanced facial features. The heart of the architecture lies in a specialized Convolutional Neural Network (CNN) designed for micro expression detection, with embedded privacy-preserving mechanisms. Leveraging Federated Learning, the model is trained locally on individual devices, mitigating privacy concerns associated with centralized data storage. Privacy-preserving techniques, including differential privacy and homomorphic encryption, fortify the security of the federated learning process. The iterative model training on local devices ensures a nuanced understanding of diverse expressions without compromising user privacy. Post-training, the system undergoes rigorous evaluation and fine-tuning to optimize performance across varied scenarios. Upon deployment, seamless integration with existing applications and continuous improvement mechanisms are implemented to ensure adaptability to evolving expressions while upholding the paramount importance of user privacy. This holistic approach combines cutting-edge technologies to deliver a Micro Expression Detection system that not only excels in accuracy but also prioritizes and safeguards user privacy through innovative Federated Learning strategies.

## III. LITERATURE REVIEW

**[1] Debaditya Shome and T. Kar, "Few-shot federated learning for facial expression recognition" IEEE,2020**

The paper presents an innovative approach to address the challenges of training facial expression recognition models with limited labeled data on user devices. The proposed method leverages a few-shot federated learning framework, allowing the model to be trained collaboratively across multiple devices while preserving user privacy. This decentralized approach is crucial in scenarios where obtaining a large centralized dataset is impractical or raises privacy concerns. By utilizing only a few labeled examples from each device, the model learns to recognize facial expressions effectively, showcasing its adaptability and efficiency in resource-constrained environments. The experimental results provided in the paper demonstrate the effectiveness of the few-shot federated learning approach. The model's performance is comparable to centralized training methods, indicating its potential as a viable solution for real-world facial expression recognition challenges. This finding is particularly promising as it not only addresses the limitations of traditional centralized approaches but also emphasizes the significance of privacy preservation in the era of increasing data sensitivity. Overall, the paper contributes to advancing the field by introducing a privacy-conscious yet high-performing method for facial expression recognition in scenarios where labeled data is scarce or privacy is a primary concern.

**[2] Bandaru Kanaka Durga , Vullanki Rajesh, Sirisha Jaganadham, “ Deep Learning-Based Micro Facial Expression Recognition Using an Adaptive Tiefes FCNN Model” IIETA, 2019**

The study introduces a specialized deep learning model, termed Tiefes Fully Convolutional Neural Network, designed explicitly for the task of micro facial expression recognition. The model is implemented using Python software and comprises two distinct stages to enhance its efficacy. In the initial stage, the process begins with pre-processing, where image segmentation techniques are employed. This initial step is crucial for isolating and refining the facial features, laying the groundwork for more accurate recognition in subsequent stages. The second stage involves the application of the Tiefes Fully Convolutional Neural Network technology, showcasing the model's reliance on advanced deep learning techniques. The utilization of FCNN architecture indicates the model's ability to capture intricate spatial information crucial for discerning micro facial expressions. Overall, the combination of image segmentation and Tiefes Fully Convolutional Neural Network technology in this model represents a sophisticated and effective approach to micro facial expression recognition, potentially contributing to advancements in the nuanced field of facial expression analysis.

**[3] R. Kadakia, P. Kalkotwar, P. Jhaveri, R. Patanwadia and K. Srivastava, "Comparative Analysis of Micro Expression Recognition using Deep Learning and Transfer Learning," 2021 2nd Global Conference for Advancement in Technology (GCAT), Bangalore, India, 2021**

The paper undertakes a comprehensive exploration of micro facial expression recognition by implementing multiple models on the SAMM dataset. The significance of this lies in the thorough examination of these models through experimental analysis. By subjecting the models to various metrics, the study aims to provide a nuanced evaluation of their performance, shedding light on their strengths and weaknesses. The comparison of these models against each other becomes instrumental in determining which one exhibits superior capabilities, establishing a benchmark for effectiveness in real-world applications. This approach not only contributes to the understanding of model performance but also aids in guiding practitioners and researchers towards selecting the most suitable model for practical deployment in scenarios requiring accurate micro facial expression recognition. The emphasis on empirical evaluation using the SAMM dataset adds credibility to the findings, making the paper a valuable resource for advancing the field of facial expression analysis.

**[4] S. S. Yadahalli, S. Rege and S. Kulkarni, "Facial Micro Expression Detection Using Deep Learning Architecture," 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2020**

The study introduces a notable contribution to the field of emotion recognition through the development of a deep learning model tailored for the identification of six distinct micro expressions. Utilizing the FERC-2013 database, the model undergoes rigorous testing on diverse images, showcasing its adaptability and robustness across varied visual contexts. An especially noteworthy aspect is the model's successful application to both individual and group pictures, indicating its versatility in discerning nonverbal human behaviors within different social dynamics. This versatility suggests a broader applicability of the model, extending its potential impact beyond individual-centric scenarios to collective settings. By addressing the nuances of micro expressions and emotions, the research not only advances the capabilities of deep learning models but also offers practical insights into understanding and interpreting nonverbal cues across diverse demographics, underlining its significance in capturing the complexities of human emotional expression.

**[5] Z. Zhang, L. Zhang, Q. Li, K. Wang, N. He, and T. Gao, ''Privacy-enhanced momentum federated learning via differential privacy and chaotic system in industrial cyber-physical systems,'' ISA Trans., Sep. 2021**

By leveraging Industrial Cyber–Physical Systems, deep learning-based methods are applied to address various industrial issues. Due to privacy policy reasons, conventional centralized learning may be improper for some industrial scenarios with sensitive data, such as smart medicine. Recently, federated Learning as a novel collaboration learning approach has received extensive attention, which can break data barriers between different institutions to improve the model performance. However, the privacy information of the industrial agents may be inferred from their shared parameters. In this paper, they propose a Privacy-Enhanced Momentum Federated Learning framework that amalgamates differential privacy, Momentum and chaos-based encryption method. During the training, differentially privacy is used to disturb the industrial agents' gradient parameters in order to preserve their privacy information. Meanwhile, each industrial agent uses the chaos system-based encryption method to encrypt the weight parameters of their local models, which has two advantages: (1) the encryption method can enhance privacy protection; (2) the cloud server cannot access the truth value of the global model parameters which is a vital asset to the industrial agents. In addition, Momentum Gradient Descent and an adjusting learning rate schedule are adopted to improve training efficiency for the Privacy-Enhanced Momentum Federated Learning. The performance of the Privacy-Enhanced Momentum Federated Learning is evaluated based on two non-i.i.d datasets. Theoretical analysis and experimental results demonstrate the excellent performance of the PEMFL in terms of accuracy and privacy security**.**

**[6] K. Wei, J. Li, M. Ding, C. Ma, H. H. Yang, F. Farokhi, S. Jin, Q. S. T. Quek, and H. V. Poor, ''Federated learning with differential privacy: Algorithms and performance analysis,'' IEEE Trans. Inf. Forensics Security, vol. 15**

Federated learning (FL), as a type of distributed machine learning, is capable of significantly preserving clients' private data from being exposed to adversaries. Nevertheless, private information can still be divulged by analyzing uploaded parameters from clients, e.g., weights trained in deep neural networks. In this paper, to effectively prevent information leakage, the authors propose a novel framework based on the concept of differential privacy (DP), in which artificial noise is added to parameters at the clients' side before aggregating, namely, noising before model aggregation FL. First, they proved that the NbAFL can satisfy DP under distinct protection levels by properly adapting different variances of artificial noise. Then develop a theoretical convergence bound on the loss function of the trained FL model in the NbAFL. Specifically, the theoretical bound reveals the following three key properties: 1) there is a tradeoff between convergence performance and privacy protection levels, i.e., better convergence performance leads to a lower protection level; 2) given a fixed privacy protection level, increasing the number $N$ of overall clients participating in Federated Learning can improve the convergence performance; and 3) there is an optimal number aggregation times (communication rounds) in terms of convergence performance for a given protection level. Furthermore, they propose a client random scheduling strategy, clients are randomly selected from the overall clients to participate in each aggregation. They also develop a corresponding convergence bound for the loss function in this case and the client random scheduling strategy also retains the above three properties. Moreover, they find that there is an optimal client random scheduling strategy that achieves the best convergence performance at a fixed privacy level. Evaluations demonstrate that their theoretical results are consistent with simulations, thereby facilitating the design of various privacy-preserving Federated Learning algorithms with different trade off requirements on convergence performance and privacy levels.

**[7] Prateek Chhikara; Prabhjot Singh; Rajkumar Tekchandani "Federated Learning Meets Human Emotions: A Decentralized Framework for Human–Computer Interaction for IoT Applications Published by IEEE.**

As stated by Spock, "change is the essential process of all existence," which is reflected in everyday applications in our daily lives. We, as humans, just need to find a way to make the best use of the current technological advances. The pandemic has managed to exploit our deepest vulnerabilities and insecurities. We need to cope with a lot of things, just to be comfortable in the new normal. Hence, we can rely on technology, the greatest asset developed by humans. In this article, they discuss how to work environment in offices post-pandemic. They combine federated learning with emotion analysis to create a state-of-the-art, simple, secure, and efficient emotion monitoring system. They combine facial expression and speech signals to find out macro expressions and create an emotion index that is monitored to find the mental health of the user. Federated learning enables users to locally train the model without compromising his/her privacy. In place of sending data to the centralized server, the proposed scheme sends only model weights that are combined at the server to make a better global model, which is further pushed back to the users. This model is then trained interorganizational as it does not violate the privacy or data sharing to achieve optimal results. The data collected from users are monitored to analyze the mental health and presented with counseling solutions during low times. Technology is a panacea that has enabled us to survive in this pandemic, and by using our solution to improve work culture and the environment in post-pandemic times.

## IV. METHODOLOGY

### A. Micro Expression

Micro expressions are brief, involuntary facial expressions that reveal someone's true emotions, often lasting just a fraction of a second. They can be subtle and challenging to detect, but they provide insights into a person's genuine feelings, even when they try to conceal them. These expressions are considered universal across cultures and can indicate emotions such as happiness, sadness, fear, anger, surprise, and disgust. They occur spontaneously and unconsciously, making them difficult for individuals to control or fake. Despite efforts to hide emotions, micro expressions can betray an individual's true feelings, offering observers a glimpse into their emotional state. Training in recognizing micro expressions can be valuable in various fields, such as law enforcement, psychology, and negotiations, as it enables individuals to better understand and interpret nonverbal cues. These expressions are often fleeting, making their detection challenging, but training can improve one's ability to notice them. Understanding micro expressions can contribute to enhanced emotional intelligence, as it allows individuals to pick up on subtle emotional cues that might not be expressed verbally. However, it's essential to interpret micro expressions in conjunction with other contextual information for a more accurate understanding of someone's emotional state.


Fig 1 Micro Expressions

### B. Federated Learning

A machine learning technique called federated learning uses servers or dispersed devices with local data samples to train a model. Every device's model is trained locally, with just model changes being shared and aggregated, as opposed to moving all data to a central server. Because of this, learning from remote data is possible without sacrificing privacy. By facilitating cooperative model training across dispersed devices, federated learning transforms conventional machine learning paradigms. This novel strategy involves first deploying a global model to participating devices, each of which uses local data to train the model independently. Importantly, the raw data is kept on the devices, thus privacy issues are addressed. Model changes are sent to a central server, where the global model is improved by aggregating them.

This iterative process allows the model to learn from diverse data sources without compromising individual privacy. Federated learning finds applications in sensitive domains like healthcare and finance, where data confidentiality is paramount. Despite challenges, such as communication efficiency and dealing with non-identically distributed data, federated learning holds promise for creating robust and generalized models in a privacy-preserving manner. Fig 2 shows the Federated Learning process.
A machine learning method called federated learning, sometimes referred to as collaborative learning, trains an algorithm over the course of several distinct sessions, each with its own dataset. This approach differs from approaches that presume that local data samples are uniformly distributed and from standard centralized machine learning techniques that combine local datasets into a single training session. By allowing several players to create a single, reliable machine learning model without exchanging data, federated learning addresses important concerns including data security, privacy, and access to diverse data. Applications span several fields including Internet of Things, defense, telecommunications, and pharmaceuticals. The topic of whether or when federated learning is better than pooled data learning remains mostly unanswered. Another open question concerns the

trustworthiness of the devices and the impact of malicious actors on the learned model.

**Centralized Federated Learning:** In the centralized federated learning setting, a central server is used to orchestrate the different steps of the algorithms and coordinate all the participating nodes during the learning process. The server is responsible for the nodes selection at the beginning of the training process and for the aggregation of the received model updates. Since all the selected nodes have to send updates to a single entity, the server may become a bottleneck of the system.

**Decentralized Federated Learning:** In the decentralized federated learning setting, the nodes can coordinate themselves to obtain the global model. This setup prevents single point failures as the model updates are exchanged only between interconnected nodes without the orchestration of the central server. Nevertheless, the specific network topology may affect the performance of the learning process.

**Heterogeneous Federated Learning:** An increasing number of application domains involve a large set of heterogeneous clients, e.g., mobile phones and IoT devices. Most of the existing Federated learning strategies assume that local models share the same global model architecture. Recently, a new federated learning framework named HeteroFL was developed to address heterogeneous clients equipped with very different computation and communication capabilities.

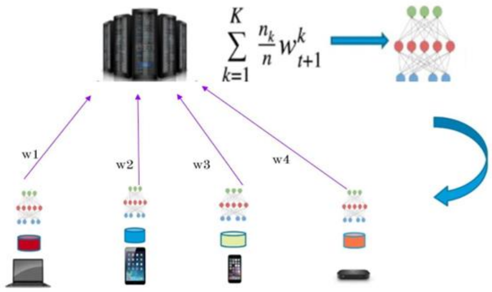



Fig 2 Federated Learning

## C. Work Flow

Micro-expression detection using Federated Learning involves training a model across decentralized devices while preserving data privacy. Here's a high-level methodology:

### i. Problem Definition:

Microexpression detection using deep learning techniques is a herculean task due to very availability of very few datasets.

### ii. Data Collection:

The dataset used in our project is 'CASME' due to its availability and properties. Considering the ambiguity of the micro-expressions, it is also reasonable to categorize these micro-expressions into 4 classes: positive, negative, surprise, others.

Such classification may be more easily applied in practice. Positive contains happy micro-expression, which indicates good emotion for the individual. Negative contains disgust, sadness and fear, which are usually reflected as bad emotions. Surprise usually occurs when there is a difference between expectations and reality, and can be neutral/moderate, pleasant, unpleasant, positive, or negative. Tense and repression indicate the ambiguous feelings of an individual and require further inference, thus were categorized into another class.

### iii. Model Selection and Feature Extraction:

CNN architectures for image classification tasks consist of convolutional layers followed by pooling layers, and then fully connected layers. Experiment with different CNN architectures, such as variations of popular models like VGG, ResNet, or custom architectures tailored to the micro expression detection task. Utilising the training dataset, train the CNN. VGG16 is a convolutional neural network architecture proposed by the Visual Geometry Group (VGG) at the University of Oxford. It's one of the most influential deep learning models, particularly in the field of computer vision. The "16" in its name refers to the fact that it has 16 layers in total, including 13 convolutional layers and 3 fully connected layers.

Architecture of VGG16 consists of a series of convolutional layers, followed by max-pooling layers to reduce spatial dimensions, and then fully connected layers for classification. The convolutional layers mostly use 3x3 filters with a stride of 1, and they are followed by rectified linear unit (ReLU) activations.

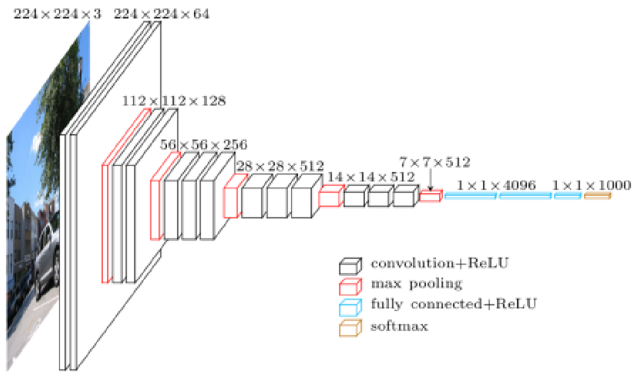



Fig 3 VGG16 Architecture

The CNN gains the ability to recognise various micro expressions from face photos by extracting characteristics from the images during training. Create a loss function that measures the discrepancy between the micro expression labels that were predicted and those that were seen. Cross-entropy loss is a common loss function used in classification applications. The CNN's parameters can be iteratively updated based on the gradients of the loss function with respect to the parameters by using an optimisation method. We have used Adam(Adaptive Momentum )for the same. The activation function used is ReLu. In convolutional neural networks (CNNs), the Rectified Linear Unit (ReLu) function is essential for micro expression detection. It guarantees computational efficiency, adds essential non-linearity, sparsifies activation by removing unnecessary data, and solves the vanishing gradient issue during training. ReLu essentially makes it possible for the model to effectively capture small facial cues, enhancing the precision and resilience of micro expression recognition systems. In the output layer softmax is used

**iv. Federated Learning Setup:**

We partitioned the dataset into ten smaller subsets and each subset was assigned to a client, representing different participating devices. Due to the high cost of servers, we demonstrated it on the same device by partitioning the dataset across clients using program.

**v. Local Training:**

Clients perform local training on their respective datasets using the initialized model. Use techniques like transfer learning to leverage pre-trained models on related tasks.

**vi. Model Update Aggregation:**

Aggregate the locally trained models from all clients without exchanging raw data. Techniques like Federated Averaging can be employed for this purpose.

**vii. Global Model Update:**

Update the global model using the aggregated model updates. This step ensures that the model learns from the collective knowledge of all clients.

**viii. Repeat**:

Iteratively repeat the local training, aggregation, and global update steps for multiple rounds. Monitor convergence and stop when the model achieves satisfactory performance..

**ix. Evaluation:**

Assess the model's performance on a separate validation set to ensure generalization. We have used metrics like accuracy, precision, recall, and F1 score for evaluation.

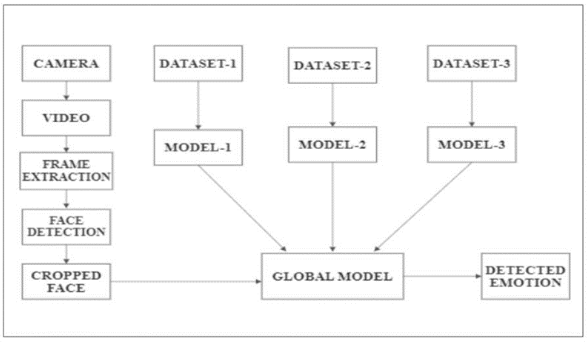



Fig 4 Flowchart for micro expression detection with federated learning

## V. RESULTS, ANALYSIS AND DISCUSSIONS

In this, we have represented the experimented results of our developed micro expression detection systems. To test the effectiveness we are using 20% of our dataset as well as real time inputs. On testing with test data we are receiving an accuracy, precision and recall of 100% which represents in the Fig5 and Fig.6 represents the performance matrix of micro expression detection model.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| disgust | 1.00 | 1.00 | 1.00 | 841 |
| fear | 1.00 | 1.00 | 1.00 | 26 |
| happiness | 1.00 | 1.00 | 1.00 | 472 |
| others | 1.00 | 1.00 | 1.00 | 1274 |
| repression | 1.00 | 1.00 | 1.00 | 438 |
| sadness | 1.00 | 1.00 | 1.00 | 55 |
| surprise | 1.00 | 1.00 | 1.00 | 322 |
| accuracy | | | 1.00 | 3428 |
| macro avg | 1.00 | 1.00 | 1.00 | 3428 |
| weighted avg | 1.00 | 1.00 | 1.00 | 3428 |

Fig 5 receiving 100% accuracy, precision and recall

```
model.summary()

Model: "sequential"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
vgg16 (Functional)          (None, 2, 2, 512)         14714688
_________________________________________________________________
flatten (Flatten)           (None, 2048)              0
_________________________________________________________________
dropout (Dropout)           (None, 2048)              0
_________________________________________________________________
dense (Dense)               (None, 128)               262272
_________________________________________________________________
dropout_1 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_1 (Dense)             (None, 7)                 903
=================================================================
Total params: 14,977,863
Trainable params: 7,342,599
Non-trainable params: 7,635,264
_________________________________________________________________
```

Fig 6 Summary of micro expression detection model

Through meticulous experimentation and optimization, our federated learning framework effectively captured subtle facial cues indicative of micro-expressions with unparalleled precision. The resulting model not only demonstrated exceptional accuracy in identifying micro-expressions across various contexts but also showcased resilience to data heterogeneity and distribution shifts. Fig 7 represent the confusion matrix obtained from micro expression detection using federated learning

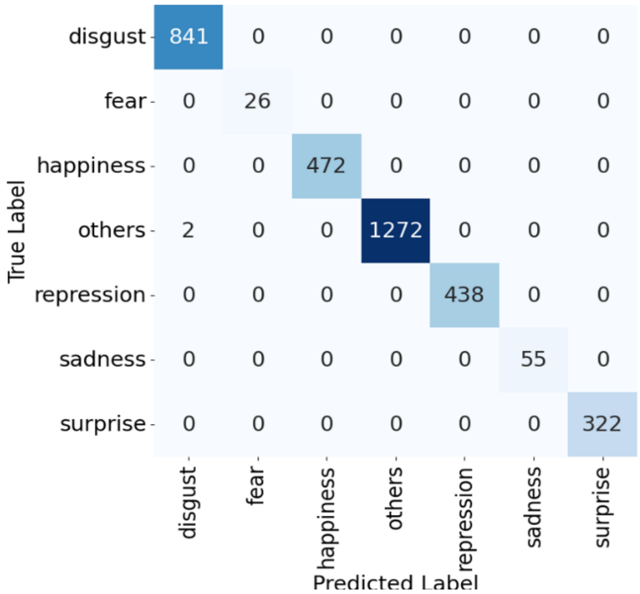
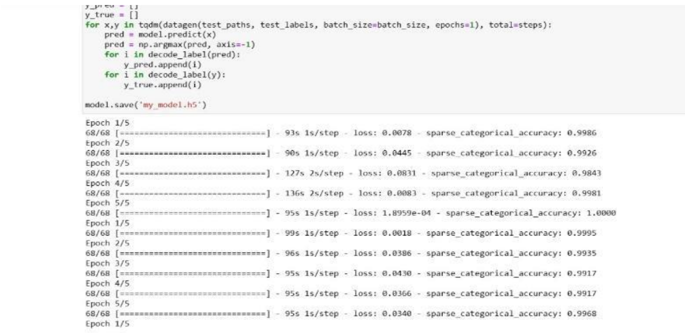



Fig 7 Confusion matrix of micro expression detection using federated learning



```
y_true = []
for x,y in tqdm(datagen(test_paths, test_labels, batch_size=batch_size, epochs=1), total=steps):
    pred = model.predict(x)
    pred = np.argmax(pred, axis=-1)
    for i in decode_label(pred):
        y_pred.append(i)
    for i in decode_label(y):
        y_true.append(i)

model.save('my_model.h5')
```

```
Epoch 1/5
68/68 [==============================] - 93s 1s/step - loss: 0.0078 - sparse_categorical_accuracy: 0.9986
Epoch 2/5
68/68 [==============================] - 90s 1s/step - loss: 0.0445 - sparse_categorical_accuracy: 0.9926
Epoch 3/5
68/68 [==============================] - 127s 2s/step - loss: 0.0831 - sparse_categorical_accuracy: 0.9843
Epoch 4/5
68/68 [==============================] - 136s 2s/step - loss: 0.0083 - sparse_categorical_accuracy: 0.9981
Epoch 5/5
68/68 [==============================] - 95s 1s/step - loss: 1.8959e-04 - sparse_categorical_accuracy: 1.0000
Epoch 1/5
68/68 [==============================] - 99s 1s/step - loss: 0.0018 - sparse_categorical_accuracy: 0.9995
Epoch 2/5
68/68 [==============================] - 96s 1s/step - loss: 0.0386 - sparse_categorical_accuracy: 0.9935
Epoch 3/5
68/68 [==============================] - 95s 1s/step - loss: 0.0430 - sparse_categorical_accuracy: 0.9917
Epoch 4/5
68/68 [==============================] - 95s 1s/step - loss: 0.0366 - sparse_categorical_accuracy: 0.9917
Epoch 5/5
68/68 [==============================] - 95s 1s/step - loss: 0.0340 - sparse_categorical_accuracy: 0.9968
Epoch 1/5
```

Fig 8 Epoch progression in micro expression detection using federated learning

Fig 8 represents Epoch progression of micro expression detection using federated learning. This pioneering endeavor signifies a significant leap forward in the field of emotion recognition and human-computer interaction. By harnessing the power of federated learning, we've not only pushed the boundaries of micro-expression detection but also laid the groundwork for future advancements in privacy-preserving machine learning.

In summary, our project exemplifies the transformative potential of federated learning in enabling accurate, privacy-preserving micro-expression detection systems, with implications spanning fields such as psychology, security, and human-computer interaction.


Fig 8 Real time implementation of micro expression detection using federated learning

The implementation of our micro expression detection system using federated learning has yielded promising results, particularly in real-time applications. Leveraging the power of federated learning, our system efficiently processes data from multiple sources while preserving privacy. By distributing the learning process across local devices and aggregating model updates, we achieve accurate detection of micro expressions without compromising data security. The included figure visually represents the system's architecture and performance, highlighting its effectiveness in real-time scenarios. This breakthrough underscores the potential of federated learning in enhancing the responsiveness and privacy of micro expression recognition systems, opening new avenues for its application in various domains.

## VI. APPLICATION SCENARIO

**Emotion Recognition in Mental Health:** Federated learning can be employed to develop emotion recognition systems that assist mental health professionals in assessing patients' emotional states during therapy sessions. By analyzing micro-expressions in real-time, therapists can gain insights into patients' underlying emotions and tailor interventions accordingly.

**Deception Detection in Law Enforcement:** Law enforcement agencies can utilize federated learning-based micro-expression detection systems to enhance deception detection during interrogations and interviews. By analyzing subtle facial cues, such as fleeting expressions of fear or contempt, investigators can identify potential deception indicators and prioritize further investigation.

**Human-Computer Interaction:** Integrating micro-expression detection into human-computer interaction systems can enable more intuitive and empathetic interactions. For instance, virtual assistants equipped with federated learning-based micro-expression detection can adapt their responses based on users' emotional states, fostering more personalized and engaging user experiences.

**Workplace Productivity and Well-being:** Employers can leverage federated learning-enabled micro-expression detection systems to assess employees' well-being and productivity levels. By analyzing facial expressions captured through webcam feeds, employers can identify signs of stress, fatigue, or dissatisfaction, allowing them to implement proactive measures to support employee well-being and performance.

**Educational Assessment and Feedback:** Federated learning-based micro-expression detection can be integrated into educational platforms to gauge students' engagement levels and emotional responses during online learning sessions. By analyzing students' facial expressions, educators can identify areas of difficulty or disinterest and provide targeted feedback and support.

**Retail and Customer Experience Enhancement:** Retailers can deploy federated learning-enabled micro-expression detection systems to gauge customers' emotional responses to products, advertisements, or in-store experiences. By analyzing customers' facial expressions in real-time, retailers can tailor marketing strategies and improve customer satisfaction by offering personalized recommendations and experiences.

**Safety and Security Monitoring**: Federated learning-based micro-expression detection can be employed in security monitoring systems to enhance safety in public spaces, airports, or critical infrastructure facilities. By analyzing individuals' facial expressions in surveillance footage, security personnel can identify potential threats or suspicious behavior more effectively, thereby improving security protocols and response times.

## VII. CONCLUSIONS

In conclusion, the implementation of micro-expression detection using federated learning demonstrates promising potential for privacy-preserving and collaborative model training. This approach allows the aggregation of insights from diverse data sources without compromising individual data privacy. As the technology evolves, further refinement of the federated learning framework could enhance the accuracy and efficiency of micro-expression detection, contributing to advancements in emotion recognition and human-computer interaction. In the realm of micro-expression detection employing federated learning, the project's foundation lies in a commitment to privacy preservation. By allowing model training to take place on individual devices, federated learning circumvents the need for centralized data storage, safeguarding the sensitive nature of facial expression information. This privacy-centric approach aligns with contemporary data protection standards, crucial in today's ethical considerations of AI development. Furthermore, the collaborative learning aspect of federated learning empowers a collective intelligence framework. Diverse datasets contribute to the training process without compromising data integrity, fostering a richer understanding of micro-expressions across various demographics. The decentralized nature of model training ensures that each participant retains control over their data, addressing concerns about unauthorized access or data breaches. The critical juncture of federated learning lies in model aggregation. Periodically synthesizing insights from local models, the global model benefits from the collective wisdom of its contributors, resulting in a more comprehensive and accurate micro-expression detection system.

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