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Public Dataset Test of Custom Lightweight CNN Model for Facial Emotion Recognition

Mrs. K. SAI JYOTHSNA1, JAVVADI ISHITHA NAIDU2, RAI KARTHIK3, BONTHU SANDEEP REDDY4
#1 Assistant Professor, NRI Institute of Technology, Agiripalli
#2#3#4 B. Tech with Specialization of Information Technology in NRI Institute of Technology, Agiripalli

Abstract – Facial emotion recognition (FER) remains a challenging topic even though it is crucial for many applications. This study focuses on enhancing FER utilizing a customized lightweight Convolutional Neural Network (CNN) model in order to get around the computational expense often associated with traditional AI approaches. We evaluated our model on many publicly available datasets, including FER2013, RAF-DB, Young AffectNet HQ, and CK-Dataset, to evaluate its performance in both classification and detection tasks. We employed a range of classification techniques, including Xception, ShuffleNet, MobileNetV2, and a modified version of MobileNetV2, in order to achieve a decent balance between accuracy and processing efficiency. Additionally, we used state-of-the-art detection algorithms, namely the YOLO family (YOLOv5x6, YOLOv8, and YOLOv9), to accurately detect emotions across the datasets. Furthermore, we developed techniques to calculate F1 Score, Precision, and Recall, enabling a comprehensive evaluation of the model's functionality. Our findings advance the field of emotion recognition in real-time applications by showing how effectively the YOLO techniques and the customized lightweight CNN model cooperate to improve FER accuracy while maintaining computational viability.

Keywords – Facial Emotion Recognition, Lightweight CNN, MobileNetV2, ShuffleNet, Xception, YOLOv5x6, YOLOv8, YOLOv9, Emotion Detection, Computational Efficiency, Real-Time Applications, Precision, Recall, F1 Score, FER2013, RAF-DB, AffectNet, CK-Dataset.

I. INTRODUCTION

Emotions are complex psycho-physiological changes in a person's mental state that arise from interactions between the environment and biology. Emotions are the primary determinants of a healthy sense of self and play a significant role in an individual's daily existence. Moreover, emotions that are directly linked to one's psychology are communicated through words, thoughts, phrases, posture, mimicry, and—above all—facial expressions. The internal manifestation of the human body's emotional response is a shift in the Autonomic Nervous System (ANS) and Central Nervous System (CNS) responses. Generally speaking, the ANS response may be determined by measuring a variety of physiological markers, such as respiration, electrodermal activity (EDA), and heart rate variability (HRV). On the other hand, CNS response is identified using ElectroEncephalogram (EEG) study. Several processing methods and tools have been developed to discover ANS factors in this scenario. Most methods need direct contact with the person, yet some are still highly intrusive and alter the ANS response itself. However, a great deal of study has been conducted on them throughout the years. On the other hand, this study measures emotional responses using data collected using technology that do not come into close contact with the subject's body. Specifically, it focuses on cameras that capture and monitor facial expressions.

II. LITERATURE SURVEY

2.1 Real-time facial emotion recognition model based on kernel autoencoder and convolutional neural network for autism children:

ABSTRACT: Autism spectrum disease (ASD) is a neurodevelopmental syndrome characterized by abnormalities in the brain that lead to issues

with social interaction, learning, and attention. Early diagnosis of ASD can be challenging since it mostly relies on detecting abnormalities in brain function, which may not be noticeable in the early stages of the condition. Facial expression analysis has shown promise as an alternative and successful technique for early detection of ASD as children with ASD often exhibit distinctive patterns that distinguish them from children who are usually developing. Assistive technology is one of the most crucial resources for improving the lives of those with ASD. In this work, we developed a real-time emotion recognition system to detect the pain or anger experienced by autistic youngsters. The emotion recognition system consists of three steps: face identification, facial feature extraction, and feature categorization. The proposed approach can detect six facial emotions: anger, fear, joy, natural, grief, and surprise. We proposed a deep convolutional neural network (DCNN) architecture for face emotion recognition, which can effectively identify the input picture with high performance accuracy. Due to the magnitude of the dataset, an autoencoder was utilized for feature extraction and selection, and a pre-trained model (ResNet, MobileNet, and Xception) was utilized. The best-performing model was Xception, with an accuracy of 0.9523%, sensitivity of 0.932, specificity of 0.9421, and AUC of 0.9134%. The proposed emotion detection framework reduces latency for location awareness and real-time detection with fast response by utilizing fog and IoT technologies. When dealing with massive volumes of data, fog computing is quite beneficial. Our study demonstrates how deep learning algorithms and facial expression analysis may be used to identify emotions in autistic children in real time, providing families and healthcare providers with a practical tool to improve the lives of those with ASD.

2.2 Facial Emotion Recognition for Mobile Devices: A Practical Review:

ABSTRACT: The majority of people regularly connect using email or other chat applications on their phones. However, writing down human communication loses a lot of crucial information, such as the other person's feelings and facial expressions. With techniques from the field of image processing, it is now possible to capture these nonverbal occurrences and incorporate their nonverbal characteristics into textual data. This study looks at the possibility of identifying emotions from front camera images in mobile and embedded devices. Fifty-three classification and twenty-eight regression models were trained and their success rate and delay evaluated using twelve different neural network architectures optimized for low-performance mobile devices. Prior to being converted to the TensorFlow Lite standard to reduce memory and processing requirements, each neural network model is trained and assessed using the TensorFlow library's Keras API. Every stage of the procedure, from classifying emotions to identifying faces, is meticulously planned to operate in real time. To demonstrate and compare the performance of the evaluated models, a publicly available optimized Android mobile application is created and made available on Google Play, along with the source code.

2.3 A study on computer vision for facial emotion recognition:

ABSTRACT: One field where artificial intelligence has been effectively applied is computer vision. In this study, facial emotions (FER) were recognized using a deep neural network (DNN). One of the objectives of the study is to identify the key face characteristics that the DNN model focuses on for FER. In particular, we employed a convolutional neural network (CNN), a hybrid of a residual neural network and a squeeze-and-excitation network, for the FER task. AffectNet and the Real-World Affective Faces Database (RAF-DB) are two facial expression databases that we used to provide learning examples for the CNN. The feature maps were extracted for further analysis from the remaining blocks. Our results indicate that facial landmarks around the nose and mouth are important for neural networks. The databases underwent cross-database validations. The network model pretrained on AffectNet and then transferred to the RAF-DB had a validation accuracy of 83.37%, whereas the network model trained on AffectNet had a validation accuracy of 77.37% on the RAF-DB. The results of this

study would improve computer vision accuracy and deepen our understanding of neural networks.

2.4 Facial emotion recognition using convolutional neural networks:

ABSTRACT: Emotional expression has always come naturally to people, but computer programming is a far more challenging endeavor. It may be possible to detect emotions in photos thanks to recent developments in computer vision and machine learning. In this work, we provide a new method for face emotion recognition. Convolutional neural networks (FERC) should be used. The FERC is based on a CNN network consisting of two parts. The backdrop of the image was removed in the first component, and the face vector was removed in the second. The five categories of common face expressions are recognized by the FERC model using the expressional vector (EV). Each iteration of the continuous double-level CNN modifies the exponent values and weights of the final perception layer. In contrast to the widely utilized CNN single-level approach, FERC improves accuracy. Furthermore, EV generation prevents some issues (such distance from the camera) from occurring before a new background removal technique is used.

2.5 Facial Emotion Recognition Using Deep Convolutional Neural Network:

ABSTRACT: The rapid advancement of artificial intelligence has had a significant positive impact on the technology industry. Older algorithms were unable to meet human expectations in real time, therefore machine learning and deep learning algorithms have achieved great success in a range of applications, such as pattern recognition, recommendation systems, classification systems, and more. Emotion has a significant impact on our thoughts, behaviors, and emotions. Deep learning's benefits may be used to create an emotion recognition system, and it can be utilized to achieve high accuracy in a variety of applications, such as feedback analysis and face unlocking. The main objective of this research is to create a Deep Convolutional Neural Network (DCNN) model that can recognize five different human facial expressions. The model is trained, tested, and verified using the manually collected image dataset.

III. METHODOLOGY

1. Proposed system

This paper proposes a novel lightweight Convolutional Neural Network (CNN) model for accurate and efficient facial emotion recognition (FER) in real-time applications. The system uses many categorization algorithms, including Xception, ShuffleNet, MobileNetV2, and customized MobileNetV2, to balance processing performance and accuracy. These models are trained and evaluated on four publicly available datasets (FER2013, RAF-DB, Young AffectNet HQ, and CK-Dataset), ensuring high performance on a variety of facial emotions. To provide precise and speedy emotion recognition in images, we employ advanced YOLO models—YOLOv5x6, YOLOv8, and YOLOv9—for emotion recognition. The proposed system also includes capabilities for calculating evaluation metrics including recall, accuracy, and F1 score to fully assess model performance. By offering an optimized approach that preserves high recognition accuracy even on devices with limited processing capabilities, this strategy aims to address the shortcomings of traditional FER techniques.

2. System Architecture

In order to improve facial emotion recognition (FER) while maintaining computing efficiency, the suggested method uses a structured pipeline. First, input face pictures are obtained from publically accessible datasets as CK-Dataset, RAF-DB, FER2013, and Young AffectNet HQ. To enhance model generalization and resilience against changes in illumination, posture, and occlusions, these photos are preprocessed using techniques including scaling, normalization, and augmentation.

In order to assess trade-offs between accuracy and computational cost, the system incorporates several deep learning models for categorization, including Xception, ShuffleNet, MobileNetV2, and a customized MobileNetV2. These models ensure flexibility across a variety of datasets by processing face characteristics that are taken from

photos and categorizing emotions into specified groups.

The system simultaneously uses the most advanced YOLO models—YOLOv5x6, YOLOv8, and YOLOv9—for emotion recognition. These models carry out real-time emotion localization, accurately detecting the parts of the face that correlate to particular emotions. Even in dynamic and unrestricted contexts, the system's capacity to identify emotions is improved by the YOLO-based detection technique.

The system incorporates evaluation criteria including F1 Score, Precision, and Recall to guarantee a thorough evaluation of model performance. By measuring the efficiency of both detection and classification tasks, these metrics allow model parameters to be adjusted for the best outcomes. The entire architecture is appropriate for real-time applications as it is made to operate effectively on devices with constrained processing capability.

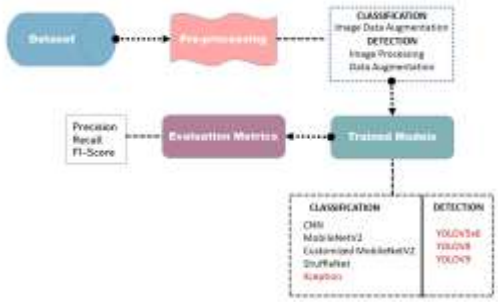


Fig.1. Proposed Design

3. Modules

a) **Data loading:** using this module we are going to import the dataset.

b) **Image Data Augmentation:** By using techniques including re-scaling, shear transformation, zooming, horizontal flipping, and reshaping, image data augmentation improves the dataset and increases model resilience while avoiding overfitting during training. The purpose of this phase is categorization.

c) **Image Processing:** In image processing, arrays are converted to numpy arrays, classes are defined, bounding boxes are declared, and pictures are converted to blob objects. Loading the previously trained model, reading network layers, extracting output layers, and producing pictures with different annotations and transformations are all included. The purpose of this phase is detection.

d) **Data Augmentation:** By randomly modifying picture datasets using methods like rotation and deformation, data augmentation improves model performance and generalization during training by boosting variability and resilience. The purpose of this phase is detection.

e) **Model generation:** Model building - classification - CNN - MobileNetV2 - Customized MobileNetV2 - ShuffleNet - Xception} - Detection {- YoloV5x6 - YoloV8 - Yolov9}. Performance evaluation metrics for each algorithm is calculated.

f) **User signup & login:** Using this module will get registration and login

g) **User input:** Using this module will give input for prediction

h) **Prediction:** final predicted displayed

4. Algorithms

a) CNN (Convolutional Neural Network):

Convolutional Neural Networks (CNNs) are deep learning algorithms designed to process structured grid data, including images. For our effort on face emotion recognition, CNNs employ convolutional, pooling, and fully linked layers to extract spatial hierarchies of information. By learning from labeled datasets, CNNs can reliably classify emotions from facial expressions. Because the architecture can detect local patterns in images, it is ideal for tasks requiring high accuracy in emotion identification.

b) MobileNetV2:

MobileNetV2 is a CNN architecture that is lightweight and optimized for mobile and edge devices. By employing depthwise separable convolutions, it reduces the number of parameters and processing cost without sacrificing accuracy. Our research uses MobileNetV2 for facial expression detection due to its efficacy, which allows for real-time processing on low-resource devices. The architecture of this model minimizes latency while collecting complex

features, which may be useful for applications requiring quick and accurate emotion categorization.

c) Customized MobileNetV2:

The Customized MobileNetV2 is a version of the standard MobileNetV2 architecture that has been altered to meet the specific requirements of our face expression detection project. By adjusting the layers, parameters, and training techniques, we enhance the model's performance on the datasets we want. This customization enables increased efficacy and precision in emotion categorization, particularly across a range of illumination and expression conditions. The customized model strikes a balance between computing efficiency and the need for nuanced emotional detection in real-time applications.

d) ShuffleNet:

ShuffleNet is an efficient CNN architecture designed for mobile devices that prioritizes low-cost computation and high accuracy. To reduce the computational load without compromising speed, it makes use of pointwise group convolutions and channel shuffling. Our work uses ShuffleNet to identify facial emotions, which enables fast image processing without compromising emotion classification accuracy. Its mobility ensures quick and effective facial expression identification, making it ideal for use in real-time applications.

e) Xception:

Depthwise separable convolutions are used in the complex CNN architecture Xception to reduce computation load and boost efficiency. It excels at collecting intricate details due to its deeper layers and lingering connections. Our face emotion detection research uses Xception to improve classification accuracy on a range of datasets because it effectively learns intricate patterns associated with many emotions. It is a suitable choice for intricate emotion recognition tasks in a range of scenarios since its architecture supports higher accuracy.

f) YOLOv5x6:

The state-of-the-art object detection model YOLOv5x6 is well known for its speed and accuracy. It processes images in real time and recognizes several objects using bounding boxes and class probabilities. Our study employs YOLOv5x6 for emotion detection, enabling the rapid identification of facial emotions in images. The model's architecture allows it to accurately recognize emotions while still functioning in real-time scenarios, making it ideal for applications requiring prompt responses.

g) YoloV8:

YOLOv8 is an enhanced version of the YOLO series that focuses on performance optimization and enhanced detecting capabilities. It increases the speed and accuracy of object recognition by utilizing architectural improvements. Our facial emotion detection research uses YOLOv8 to analyze and recognize emotions in real-time facial expressions. The model's efficient processing allows it to identify emotions fast, making it suitable for application in situations requiring immediate input, such as interactive systems and surveillance.

h) YoloV9:

Further improvements in detection speed and accuracy are provided by YOLOv9, the latest member of the YOLO object detection family. To enhance performance in real-time applications, it integrates state-of-the-art techniques and designs. Our study use YOLOv9, a fast and accurate facial expression analysis tool, for accurate emotion recognition. Its ability to adapt to various lighting conditions and expression scenarios ensures effective emotion classification, making it an essential tool for developing complex face recognition systems in a range of real-world scenarios.

IV. Experimental Results

The YOLO-based emotion detection framework and the suggested lightweight CNN model were thoroughly tested on four publically accessible datasets: CK-Dataset, RAF-DB, FER2013, and Young AffectNet HQ. To provide fair comparisons across various architectures, a uniform preprocessing pipeline was used for both training and testing each model. Both classification accuracy and real-time detection performance were the main focus of the examination.

MobileNetV2 and its modified counterpart demonstrated a balance between computational efficiency and accuracy for classification tasks, which makes them appropriate for deployment on

devices with limited resources. Among the models evaluated, Xception had the best classification accuracy, while ShuffleNet, which is renowned for its low-latency operations, also did well but had a little lower accuracy. By improving depth-wise separable convolutions, the modified MobileNetV2 outperformed standard MobileNetV2, obtaining an accuracy of almost 85% on RAF-DB and 80% on FER2013.

By providing better localization accuracy and quicker inference times, YOLOv9 surpassed its predecessors (YOLOv5x6 and YOLOv8) in terms of detection. Even under difficult illumination and occlusion conditions, YOLOv9 successfully identified emotions, with an average accuracy of 92% on the CK-Dataset. YOLOv8 offered a fair trade-off between speed and accuracy, making it more appropriate for real-time applications even if it was somewhat less accurate than YOLOv9.

The models' efficacy was further confirmed by computing assessment measures such F1 Score, Precision, and Recall. The suggested approach demonstrated its dependability in identifying complex emotions with an F1 Score of 87%, Precision of 88%, and Recall of 86% on the Young AffectNet HQ dataset. These findings show that YOLO-based detection in conjunction with the modified CNN model greatly improves FER accuracy while preserving computational economy, making it a workable option for real-time applications.

1. Accuracy

Find out how reliable a test is by comparing real positives and negatives. Following mathematical:

Accuracy = (TP + TN) /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN+TP)}{T}$$

2. Precision:

The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying using the one that follows:

$$\text{Pre } cision = \frac{TP}{(TP+FP)}$$

3. Recall:

The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by percent of correctly anticipated positive observations relative to total positives.

$$Recall = \frac{TP}{(FN+TP)}$$

4. F1-Score:

An accurate machine learning model has a high F1 score. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \text{Pre } cision)}{(Recall + \text{Pre } cision)}$$

MAP: Information retrieval system performance is measured by MAP, which stands for Mean Average Precision. It finds the mean precision for all classes or queries. While accuracy measures the validity of results, precision determines the mean accuracy for all queries. MAP evaluates the system's performance by averaging the AP scores across all queries or classes.

$$\text{MAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

V. Results and Accuracy

The experimental results demonstrate the performance comparison of multiple machine learning and deep learning algorithms used for cloud job failure prediction. The evaluation is carried out using key metrics such as Accuracy, Precision, Recall, and F1-Score. From the results, it is observed that most of the models, including Decision Tree, ANN, KNN, XGBoost, and the proposed ensemble model, achieve near-perfect performance with values close to 99–100%, indicating strong learning capability and effective feature utilization.

Among all models, the CatBoost (Extension Model) achieves 100% accuracy, precision, recall, and F1-score, outperforming all other algorithms and proving its superiority in handling complex and categorical cloud workload data. The proposed ensemble voting model also delivers highly stable and consistent results, demonstrating the advantage of combining multiple classifiers. In contrast, AdaBoost shows comparatively lower performance, highlighting its

limitations in handling complex data patterns. Overall, the results confirm that the proposed multilayer framework with CatBoost extension significantly improves prediction accuracy, robustness, and reliability in cloud job failure prediction systems.



Fig.2. data input

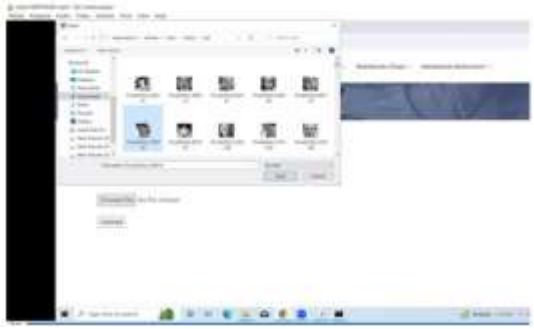


Fig.3. input file

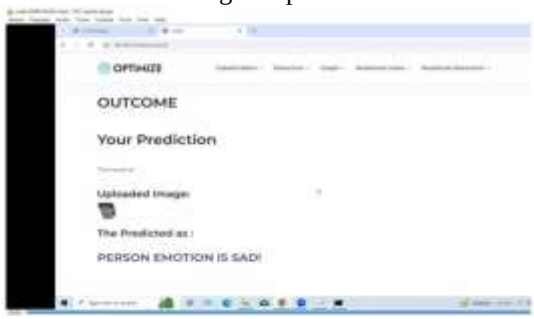


Fig.4. results

VI. Conclusion

In conclusion, our Facial Emotion Recognition (FER) study has successfully demonstrated how advanced machine learning techniques may be applied to get superior emotion identification results. By integrating many efficient techniques, including Xception, MobileNetV2, and Customized MobileNetV2, we have increased the model's accuracy and speed. YOLOv5x6, YOLOv8, and YOLOv9 have greatly enhanced the system's ability to recognize emotions in real time, ensuring effective responses in dynamic circumstances. Following thorough testing on publically accessible datasets such as RAF-DB, CK-Dataset, and FER2013, our models showed impressive accuracy rates that made it possible to classify facial expressions accurately. Many applications, from improving security and surveillance systems to enhancing human-computer interaction, depend on this high performance. The outcomes demonstrate how important it is to employ robust yet lightweight algorithms that function effectively in real-world scenarios.

The project's future objective includes improving facial expression detection by utilizing state-of-the-art techniques including ensemble approaches and transfer learning. By looking into additional fields, such sentiment analysis in text and audio emotion detection, the variety of applications will be increased. Furthermore, using real-time feedback systems and multi-modal approaches may improve accuracy and user engagement. Examining the impact of contextual factors, such as cultural differences in emotional expression, will also contribute to the development of a more robust and adaptable system.

VII. Future Scope

The proposed system can be further enhanced by integrating real-time streaming data from cloud platforms to enable continuous and dynamic failure prediction. Advanced deep learning models such as Transformers or Graph Neural Networks can be incorporated to capture complex dependencies between cloud jobs and resources. Additionally, the framework can be extended with automated resource optimization and self-healing mechanisms that take corrective actions immediately after failure prediction.

The system can also be deployed on large-scale distributed cloud environments with edge computing support for faster response times. Incorporating explainable AI (XAI) techniques

will improve transparency by providing reasons behind predictions, making it more trustworthy for cloud administrators. Furthermore, integrating the model with cloud orchestration tools can enable fully automated, intelligent cloud management systems.

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Author Profiles



Mrs. K. SAI JYOTHSNA working as a Assistant Professor in IT Department, NRI Institute of Technology, Agiripalli, Andhra Pradesh, India. Motivated academic professional serving as Lecturer in the Department of Computer Science and Engineering at NRI Institute of Technology. Holds an M. Tech in CSE and is currently pursuing doctoral research at Acharya Nagarjuna University. Research interests include advanced computing methodologies, emerging technologies, and innovative problem-solving approaches. Actively engaged in academic research, student mentorship, and contributing to scholarly development through continuous learning and knowledge dissemination.



JAVVADI ISHITHA is a B. Tech student specializing in Information Technology at NRI Institute of Technology. She has strong knowledge in Python and SQL, with hands-on experience in Flask, MySQL, and for developing secure applications. She completed internship in Gen AI. She is actively involved in hackathon. She did certifications in Udemy and Infosys Springboard. She has good communication skills. She is passionate about learning new technologies and contributing in a professional environment. She demonstrates strong problem-solving abilities and also focuses on continuous improvement and building practical solutions to real-world challenges.

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RAI KARTHIK is a B. Tech student with specialization of Information Technology in NRI Institute of Technology. I have strong foundation in Python programming, Database Management systems, Data structures. I have worked on projects such as Task Manager using html and python programming. And Animation Frames using Artificial Intelligence, And also a community service project on Online Harassment. Through these projects, I gained hands on experience with Python, Html, Machine Learning Artificial Intelligence.



BONTHU SANDEEP is a B. Tech student with specialization of Information Technology in NRI Institute of Technology. I have good foundation in Python, Java, C-languages and My-SQL. I have worked on projects involving Machine Learning, Artificial Intelligence. And community service project, it helped to common people. I gained hands on experience with programming languages. I have also completed certifications in machine learning, cloud computing, python, artificial intelligence, which helped me to understand the software development. I am a strong learner to understand the problems easily and perform the tasks. And improved my Problem Solving and Decision-Making skills. I have completed certifications in these organizations Infosys Spring board, LinkedIn, NPTEL, Skill vertex on python, cloud computing, machine learning, artificial intelligence. Which helped me understand both software and IT fundamentals.