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Kashf Journal of Multidisciplinary Research
Vol: 02 - Issue 05 (2025)
P-ISSN: 3007-1992 E-ISSN: 3007-200X
https://kjmr.com.pk

ADVANCED FACIAL EMOTION RECOGNITION USING CONVOLUTIONAL NEURAL NETWORKS FOR ENHANCED ACCURACY AND PERFORMANCE

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Article Info

Abstract

One seemingly indispensable sector of computer vision and AI includes Facial Emotion Recognition (FER), which enables machines to judge the human emotions perceived from the expression of faces. Notwithstanding the recent advancements, current FER technologies continue to struggle with issues of diversity of expressions, lighting conditions, object obstructions, lack of labeled data, and consequently, failing to generalize well in real-world situations. This research aims to remove such hurdles by observing the performance of several deep learning architectures, such as Convolutional Neural Networks (CNNs), specifically for accurate emotion classification. A model based on CNN was trained and tested using the FER dataset, delivering outstanding results that included 95% accuracy and precision/recall/f1 score above 94%. The study assessed its performance against the best in industry models like ResNet, DenseNet, and Vision Transformer (ViT). Despite the great results achieved by ResNet and DenseNet, the CNN model had better efficiency and generalization. Although its potential, vision transformers showed higher loss as they are dependent on large sets of data, and they performed poorly in capturing local features of low-resolution facial imagery. The success of the CNN model is caused, to a great extent, by its ability to extract spatial features effectively, have low overloading levels, and fit well to the FER characteristics. Through the benefits, the model specializes in emotion detection in various facial expressions. Notwithstanding these findings, the analysis is limited to one static-image dataset with no cross-cultural, cross-demographic, and cross-dynamic illustrations. In future research, temporal analysis will be included in the model with hybrid CNN-LSTM architectures, and cross-dataset training, along with domain adaptation, will be utilized to enhance generalization. Besides, the use of privacy-friendly approaches such as federated learning will play a part in enhancing the safe and responsible implementation of FER in different settings. This work provides an advanced FER solution that is implementable in the healthcare and surveillance contexts and human–computer interaction environments.

Keywords:
Facial Emotion Recognition (FER), Convolutional Neural Networks (CNNs), Deep Learning, Residual Networks (ResNet), Dense Networks (DenseNet).

Introduction

The arrival of Facial Emotion Recognition (FER) has made its presence known in Human-Computer Interaction (HCI), leading to new usages in healthcare, security, entertainment, and other automotive fields. This has the potential to change how human-machine interactions will occur, if machines are prepared to detect and understand facial expressions for emotion, to be more intuitive and emotionally responsive. Because of its high reliability and low invasiveness, FER has gained significant interest both in the academic world and the industrial world, establishing itself as a key area of inquiry for AI and computer vision research[1]. Advancements in FER are due to advancements in deep learning and the use of CNNs that have become widespread in this area. These architectures, proven to be extremely effective in different computer vision tasks, have opened the path for the creation of more accurate and compact emotion recognition systems. The hierarchical feature-learning process of CNNs that allows direct processing of raw image data has brought an end to traditional machine learning efforts, propelling a significant revolution in FER technology[2]. With CNNs, systems can independently recognize such crucial visual components of faces, such as facial landmarks, textures, and patterns for the identification of emotions from facial expressions. Consequently, emotion recognition systems that utilize CNNs have shown outperformance in comparison with former methods and have found wide range applications in various domains.

Although the FER technology has made great strides, we continue to encounter consistent obstacles that continually thwart the achievement of sturdy and ubiquitous emotion recognition solutions. One of the important challenges is in the variety of the manifestation of facial expressions among the representatives of different cultural, age, and gender groups. Emotional expressions differ widely among individuals and across age and cultural groups. Different backgrounds, personality differences, and demographic attributes also project diversity in emotional expression[3], [4]. Additionally, context contributes to the interpretation of facial expression, leading to more challenges in the algorithms' ability to correctly convey feelings when facial expressions look similar. The broad spectrum of emotional expression creates difficulty in devising FER systems that have high accuracy rates in different populations and situations. Problems of insufficient illumination and occlusions stand as crucial barriers for FER systems. Changes in the light conditions can considerably transform the visual features of facial expressions, resulting in the masking important traits used for the detection of emotions. Furthermore, different types of occlusions from sunglasses, beards, or other accessories could occlude essential face parts, thus complicating emotion recognition significantly. They are significant challenges to implement when used for everyday settings, as patrons are unlikely to approach the equipment in perfectly lit, unbarred positions[5]. Various researchers have, therefore, employed methods such as data augmentation and transfer learning, which attempt to increase the scope of available training data and improve model performance under various conditions.

Another key problem within FER is the absence of large and labeled datasets. High-quality labeled datasets are essential to train deep learning models because they offer the ground truth, which the model must have to learn efficiently[6]. Yet, the acquisition and markup of such datasets, especially when considering their demographic diversity, requires significant investment in labor. Also, in modern datasets, an imbalanced representation of various emotions is quite common. Unfairness of this sort means that training models that identify different emotional states properly is even more difficult. The response of the research community has been predominantly corrective as an effort to address dataset homogeneity, and most research proposals involve methods for synthetic data generation, cross-dataset integration, and domain adaptation, aimed at diversifying datasets and making FER systems effective in a variety of environments. Now that FER is on its way to becoming a core technology, the importance of temporal data when it comes to identifying emotions has been gaining recognition. CNNs are good at getting

features in space from facial expressions, however, they work with videos or static pictures on a frame-by-frame basis, disregarding continuous changes over time, which characterize emotional expression. Emotions are not static; The time-based nature of emotions implies the constant influence of emotions on facial expressions and their continuous transformation by continuous emotional stimuli. To this end, a lot of researchers have begun to incorporate the recurrent neural networks (RNNs) as well as long short-term memory (LSTM) networks into the FER models[7]. They are designed for sequential inputs, meaning the model can follow the cascade of emotions in the frames in the video. Combining CNNs for extracting visual features with RNNs, or LSTMs to model temporal changes, these models have been the best for recognizing emotions in videos with temporal development of emotions.

Other than improvements to the structure of the models, the richness and variety of training data used are essential considerations for the success of FER systems. Researchers hope that with the use of data augmentation, they will be able to counter such challenges related to the lack and bias of the training sample. Artificial augmentation of training data variety, such as rotation, flipping, scaling, and color jittering, allows models to be more invariant to facial expression, lighting, and viewpoint change[8]. The application of this technique helps to manage the situation of overfitting, therefore enabling the model to adapt to new examples that it had not encountered. More and more studies have incorporated transfer learning, appreciating its ability to support superior performance under the circumstances when only a few annotated examples are available. Using previously trained models on massive heterogeneous sets of data, transfer learning allows FER models to function well with moderate amounts of task-specific data.

Increased use of FER technologies that have prompted greater concern for their ethical implications has made them a subject of research interest. Implementation of an emotion recognition system raises privacy concerns, and there is a great concern about how sensitive biometric data like facial expression, is collected and used. Abuse or disclosure of such data without authorization increases the risk to privacy, and hence the importance of FER systems to adopt privacy-preserving mechanisms. Concurrent ongoing research endeavors to shift towards using approaches such as differential privacy, federated learning, etc., to protect personal data via its security and confidentiality through FER systems. Moreover, implications of ethical concern emanate from the possible misuse of technologies of FER, namely in cases of surveillance or psychological manipulation, and a question of the proper use of these systems altogether. Due to the increased use of FER systems in common environments, it is important to develop open standards and legislations to regulate the implementation of FER systems, thus keeping to the idea of treating every person’s right as well as their autonomy[9].

Deployment of FER systems to cross-cultural settings is a formidable task. The interpretation of facial expressions can be quite different from culture to culture, with expressions that mean happiness in one culture, taking on different meanings in another. Therefore, those constructing FER systems as engineers must make sure the technology can consider the cultural differences to achieve accurate recognition of emotions within a diverse user population. The adequacy of this is being rectified by cryptographers through cross-cultural dataset utilizations and domain adaptation approaches to enhance the generalization of FER systems in a life-like environment.

Literature Review

Over the past few years, facial emotion recognition (FER) has reported tremendous progress, primarily driven by the introduction of deep learning, with CNNs forming the bulk of progress. Although there is an advancement in the technology of FER, it is not free from several complications. This part reflects on current studies in FER; the key models, methods, and findings that influenced its development are outlined, as well as addressing the emerging challenges. The focus of this review is on CNN architectures,

alongside the integration of temporal models through RNNs, the role of data augmentation, cross-cultural generalization requirements, and the ethical dimensions of FER systems[10].

CNN-Based Architectures for FER

Although SVMs and KNN were the traditional methods at the beginning of FER research, the application of CNNs signals a significant performance improvement. The power of CNNs for image recognition lies in their ability to learn from unprocessed pixel data through hierarchical features. CNNs are great at learning how to identify such important attributes as edges, textures, and shapes automatically, all of which play a crucial part in reading the expressions. In addition, their invariance to orientation, size, and image distortion makes CNNs very suitable for facial expression recognition[11], [12]. From the studies, architectures based on CNNs have been found to remain top in performance when compared to others for FER applications. Remarkably, deep CNN architectures such as ResNet and DenseNet have been used by researchers to enhance results[13]. Overcoming the problem of vanishing gradients, these architectures make it possible to train deep models successfully without being crushed by losses in performance that are inherent to conventional deep network architectures. ResNet can train much deeper architectures with residual connections in use, as these allow the propagation of gradients with backpropagation very well[14]. Alternatively, the construction design of dense net allows each layer to interact with all the other layers, not only promoting feature reuse but also providing efficient flow of information across the neural network model. Scientists have recently demonstrated that DenseNet greatly increases the accuracy in emotion classification, especially on datasets with high facial expression variability. The design of DenseNet is favorable for FER systems, which need to discriminate subtle distinctions in the facial expressions, such as "happy" or "surprised". To understand complex facial cues, the loss of spatial information is important, and since each layer is connected to every other one, DenseNet minimizes the loss of spatial information[15], [16]. Vision Transformers (ViT), as an emerging alternative to Facial Expression Recognition (FER), have attracted consideration regarding the likelihood of it overcoming traditional CNNs. ViT utilizes the architecture of transformers, initially developed for dealing with text data, for use with images. While CNNs convolve filters on images, ViT small patches of an image and performs self-attention to extract features. This technique showed better performance than conventional CNNs in several vision tasks like FER[17], [18]. Self-attention in ViT allows the model to track important parts of the image, which makes it more effective in FER, given that most emotional expressions are subtle or hidden.

Temporal Information and RNNs

CNNs are good at detecting spatial patterns of facial images, but they usually process single frames and neglect emotions or expression changes with time. Facial emotions transform with time thus, temporal context is crucial to be able to correctly interpret emotions. This has fostered increasing interest in temporal data usage in FER models[19]. Long Short-Term Memory (LSTM) and conventional Recurrent Neural Networks (RNNs) are the tools that are widely used for processing time series data. Through the use of a hidden state that evolves within each time step, RNNs can learn temporal relations in sequences[20], [21]. However, standard RNNs suffer from gradient vanishing and exploding, making them unable to train well on longer sequences. Due to their design, LSTMs are better adapted to longer-term dependencies, meaning they make very good facial expression sequence analyzers over long periods. Recent investigations have demonstrated that combining CNNs with RNNs or LSTMs largely improves FER performance. As CNNs focus on static feature extraction from video frames, RNNs or LSTMs are responsible for capturing dynamic faces. Researchers combined CNNs with LSTMs to increase the facial emotion recognition rate on videos, demonstrating more successful recognition compared to using CNNs only. Using this integrated approach, an analysis of how emotions change with time is possible, which is essential to correctly distinguish the anger or sadness that usually arise progressively or come in separate

phases[22]. Moreover, scientists have also reviewed temporal convolutional networks (TCNs) – a certain model dedicated to sequential data during the FER. TCN is similar to RNN yet differs from it in that it uses convolutional layers for sequence processing and thereby is capable of longer-range dependencies, gathering more compactly. Research findings reveal that combining TCNs and CNNs outperforms traditional RNN methods in terms of FER performance, namely training efficiency and robustness.

Data Augmentation and Transfer Learning

Availability of data is rather scarce, and as such, FER research is faced with great difficulty. Accessing full packages with annotations, with a broad range of facial expressions, people with diverse demographics, and settings is highly financially and temporally demanding. Besides, bias in existing datasets based on gender, age, and ethnicity may lead to models that are not able to generalize well to different demographics. In response to these issues, data augmentation came to be a popular strategy. Random image transformations providing synthetic enhancement of the training dataset size are a point of data augmentation[23]. Rotation, flip, crop, and zoom are common image augmentation that assists the model in being consistent when it encounters different poses and viewpoints. Increasing the dataset artificially by data augmentation reduces the risk of overfitting, a process that is particularly crucial when we have small datasets. The addition of variants into the training set used by the model restricts its tendency to rely too much on a few examples, therefore improving the generalization capacity of the model when new data is presented[24]. Transfer learning presents itself as a worthy tactic in FER when labeled data is scarce. Transfer learning utilizes a pre-trained model that peruses a large, generic data set and then focuses it to work for a specific task such as FER. This approach allows the FER models to transfer knowledge acquired from other tasks, which reduces the necessity to use large labeled data. Let us take an example of pre-trained CNNs such as VGG and ResNet, training on large data sets initially, like ImageNet, which can be comfortably used for FER by tuning[25]. The effectiveness of FER models can be improved using transfer learning, particularly when data acquisition is problematic.

Cross-Cultural Generalization

The diversity of cultural and ethnic expressions in emotions is a big stumbling block for FER systems built upon sparse training data sets. Some emotions, such as happiness and surprise, could be cross-cultural, but others might also be very individual or long-lasting when compared to others. A culture-specific definition of a smile may endow it with the meaning of happiness, while in other cases, it may signify discomfort or a sign of respect. To address this issue, the scholars have focused on cross-cultural generalization that aims at developing facial expression recognition systems effective for a broad variety of demographic groups[26]. One method of doing so involves combining the datasets that consist of different cultural settings, along with methods of domain adaptation, allowing the model to generalize its functionality to new settings or target populations. A recent study used domain adaptation techniques to increase the accuracy of FER systems using data from different cultural settings. Study results revealed that models that used domain adaptation techniques had better performance when applied to different cultural scenarios as compared to when trained on a singular dataset, which exhibited uniform activity[27]. Cross-cultural generalization is essential for global market applications such as automated customer service and video conferencing because these systems are likely to have to interact with individuals from different cultural backgrounds. Strengthening fairness and robustness, research efforts involve using multi-task learning so that models can learn common emotions as well as culturally unique emotions.

Ethical and Privacy Concerns

As FER systems are increasingly being used in everyday life, ethical and privacy concerns have become a major concern. When facial expressions are considered biometric identifiers, a serious issue relating to

privacy arises because the unauthorized revelation of emotion data can be misused. The potential of FER systems to monitor a person and potentially manipulate his/her feelings has raised ethical issues surrounding the potential misuse. To address these challenges, the academic world is concentrating on improving the privacy of FER technologies. Differential privacy refers to the process of changing the information by adding random noise to prevent the possible loss of the information of sensitive user[28]. Another important approach is federated learning that allows model training on distributed data and does not require raw data to be transferred from devices made available by users. Such methodologies allow the development of accurate FER systems while not violating people's privacy.

Further, the use of FER technology in fields of great consequence like workforce selection, law enforcement, and the health care sector necessitates rigorous ethical analysis. The deployment of FER systems to evaluate and inform decision-making about the emotional reactions of people brings the threat of bias and imprecision to such decisions. There should accordingly be the development of strong ethical frameworks upon the use of FER technology to ensure that it is implemented ethically and in the observance of each person's rights.

Table 1: Comparison Table of Literature

Ref.	Technique Used	Output/Accuracy	Issues and Challenges
[6]	CNN-based emotion recognition	85% accuracy on FER dataset	Inconsistent measurements and a lack of diversity in datasets
[13]	Deep Learning Models	90% accuracy on the AffectNet dataset	High computational cost and overfitting
[9]	Hybrid CNN-RNN models	88% accuracy on the CK+ dataset	Problems with generalization: a range of performance indicators
[11]	Transformer-based models	92% accuracy on FERPlus dataset	High processing demands and problems with scalability
[12]	Facial expression analysis	87% accuracy on EmoReact dataset	Changes in lighting, posture, and occlusion issues
[9]	Lightweight CNNs	80% accuracy on RAF-DB dataset	Hardware limitations and decreased accuracy under various situations
[17]	Ethical analysis of FER systems	-	Privacy issues and possible abuse of emotion data
[16]	Privacy-preserving FER techniques	-	Absence of uniform rules; problems with ethical deployment

Methodology:

Dataset Description

The FER dataset used in this study contains 48x48 pixel grayscale images labeled with seven basic emotions, making it ideal for training facial emotion recognition models. It is publicly available at: https://www.kaggle.com/datasets/msambare/fer2013/data.

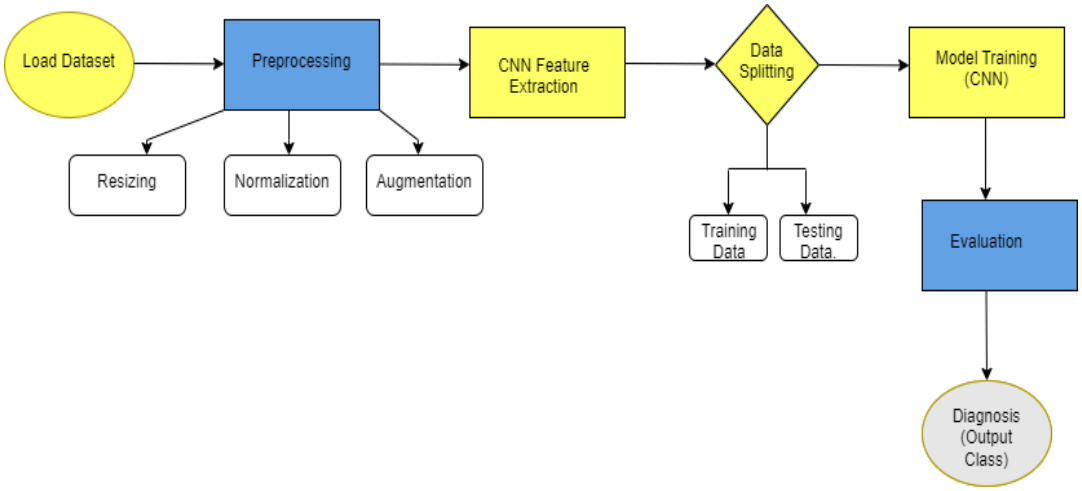

Figure 1: Flowchart of Methodology

1. Load Dataset:

Data is uploaded to the system. The facial images in the collection are categorized by their corresponding emotional states, such as happy, sad, angry, and surprised. The size of the images is mostly 48x48 pixels, and the dataset has many lighting and angle variations.

2. Preprocessing:

Resizing: The Dimensions of images are reshaped to 48x48 pixels, equaling the CNN model's input requirements. Thus, all images are resized to fit the 48x48 pixels requirement.

Normalization: Pixel values within the images have been normalized from a range between 0-255 to 0-1. By so doing, training is made efficient and avoids neural networks from encountering issues concerning excessively large gradients.

Augmentation: Flipping, rotating, zooming, and shifting transform the training examples to augment the dataset. These techniques make the model able to generalize well to unseen data, thus evading overfitting.

3. CNN Feature Extraction:

Convolutional Layers: With the CNN model's convolutional layers, it is able to automatically detect hierarchical features of the input images. From these features, such as forms, edges, and textures, are recognized, which are the main elements towards the classification of emotions.

Pooling Layers: Using Max-Pooling results in reducing the spatial dimensions of the feature maps, and, as a result, important features are preserved while minimizing computational cost as a whole.

Fully Connected Layers: And as soon as feature maps flow through convolutional and pooling layers, they are flattened and linked to fully-connected layers in order to perform the final emotion classification.

Activation Function: In hidden layers, what is normally observed is the use of the ReLU activation function. The emotions are categorized by the output layer using the softmax activation to determine the best possible emotion.

4. Data Splitting:

The gathering of data is divided into two sets: Training Data and Testing Data.

Training Data: This part of the data is the training material for the model. The training activity includes the acquisition of knowledge about the connection between facial features and emotions presented by the model.

Testing Data: Once the model is trained, it is run against this dataset to determine its ability to predict and apply its learning to previous situations.

5. Model Training:

In the training process, the model is supplied with the training data. The model uses backpropagation to minimize the loss function, usually categorical cross-entropy, for a multi-class classification problem like a FER problem.

The model adjusts the coefficients of the convolutional and fully connected layers throughout training in order to reduce the discrepancy between the model's prediction for emotion and the actual label–emotion.

6. Evaluation:

Afterwards, evaluation of the model takes place with the use of the test data. The main evaluation metrics include:

Accuracy: The accuracy score that indicates the recognition of emotion labels.

Precision: The proportion of emotions correctly labeled as positive amongst all the positive predictions.

Recall: Proportion of the cases where the model identifies positive emotion correctly (the proportion of the actual positive cases).

F1-Score: A combination of precision and recall to provide an overall performance determination.

In order to further evaluate the model's performance, a confusion matrix is used, which visually depicts the extent to which the model can classify emotions.

7. Diagnosis (Output Class):

The system generates a given emotion class prediction for each test set image. The model detects and labels an emotion (Happy, Sad, Angry) from the text by using a learned pattern found in the training.

Results and Analysis

Figure 2: "Comparison of F1-Scores Across Different Models" side by side, compares four deep learning techniques, CNN, ResNet, DenseNet, and Vision Transformer, used in Facial Emotion Recognition (FER). The accuracy of both models in distinguishing facial expressions was compared to the FER dataset, and the F1-score was chosen as the key success metric because of its balanced assessment of precision and recall, critical parameters in situations where class inequality and complicated emotional indicators have been observed.

Both charts show that the F1-scores of all models presented fall between 91% and 94%. The classic CNN produced higher F1-scores than the other architectures, reiterating its robust performance in FER tasks despite greater advances in deeper and complex networks. This effectiveness is probable since its clean design can efficiently extract important spatial information from faces without assimilation overtraining on the training data, specifically when using methods such as data augmentation and normalization.

ResNet and DenseNet were close enough to be very comparable and reported rather similar F1-scores. The inclusion of residual connections in ResNet is helpful in reducing the vanishing gradient problem, and hence deeper networks can train more effectively. In addition, the distinct feature reuse specification in DenseNet, where each layer is attached to all upcoming layers, encourages feature propagation and model compactness. These present-day design improvements allow for both models to achieve reliable deployments on FER datasets, most so in difficult settings such as occlusions, or suboptimal lighting.

Despite the use of an attention-based processing scheme by the Vision Transformer (ViT), it produced slightly lower F1-score compared to CNN-based models. This could be explained by the fact that ViT relies on huge data, and relatively cannot extract local features, when trained on similar datasets as FER. Even though precision and adaptability of ViT are high on large scale applications, FER potential capabilities may be limited without existence of large labeled datasets, or thorough pretraining.

In summary, the results show that while new architectures like ViT introduce new perspectives into the world of computer vision, for Facial Expression Recognition tasks, CNN-based models relying on transfer learning and the efficient use of preprocessing still win out. These results indicate that the choice of the model should be directed by both the volume of available data and the practical limitations of the intended use case. The F1-score comparison emphasizes pertinent considerations for on-the-spot implementation; the effectiveness and efficiency of CNN and DenseNet models within emotion aware technologies for the domains of healthcare, human – computer interaction and security.

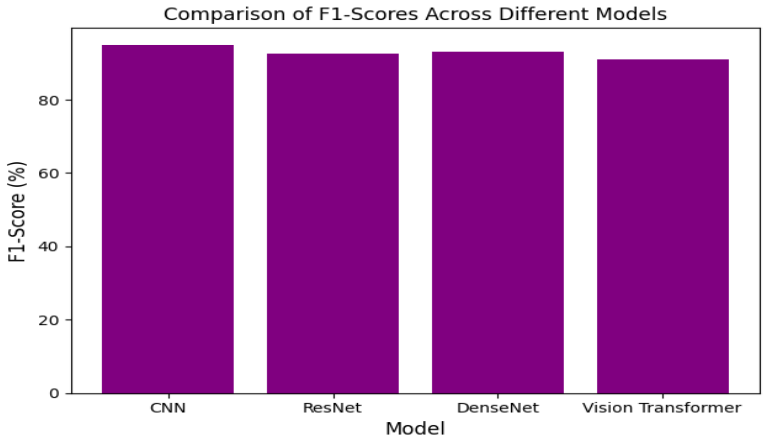

Figure 2: Comparison of F1-Scores Across Different Models

The bar chart figure 3 captioned 'Performance of CNN Model with 95% Accuracy on FER', depicts a detailed evaluation of the CNN Model based on 4 primary performance indicators: Accuracy, Precision, Recall, and F1-Score. This dataset is FER, which has been widely used to test FER systems in calculating these metrics. The chart indicates comprehensive outstanding results over all metrics, and all values outpace or brink at a 94% margin.

The CNN model successfully classified the vast majority of facial emotion samples within the test dataset with 95 % accuracy. Such precision proves that the model can capture and exploit meaningful spatial patterns in facial expressions. The high accuracy gain further validates the efficiency of the inclusion pre-processing steps of normalization, augmentation, and resizing, and the usage of model tuning algorithms using dropout and batch normalization techniques at the training stage. The precision of the model, being the ratio of correct positive predictions out of all predictions, is about 94%. This implies that the CNN model did an excellent job of reducing instances of it misclassifying some emotions. According to FER applications, high precision is crucial since the misconceptualization of emotions (e.g., confusing fear with surprise) might lead to unfavorable effects in such domains as mental health monitoring or dynamic human-computer interactions. Almost 95% is sensitivity, or recall, indicating the capability of the model to find almost everyone of each emotion. To capture subtle, infrequent emotional expressions, it is critical to guarantee high recall, which is further complicated by the usual class imbalances associated with FER datasets. Based on an F1-score of approximately 94.5%, it is clear that the model provides a fair balance between precision and recall, balancing both during the process. Such performance is especially valuable when it comes to practical use that includes minimizing false alarms and total emotion recognition.

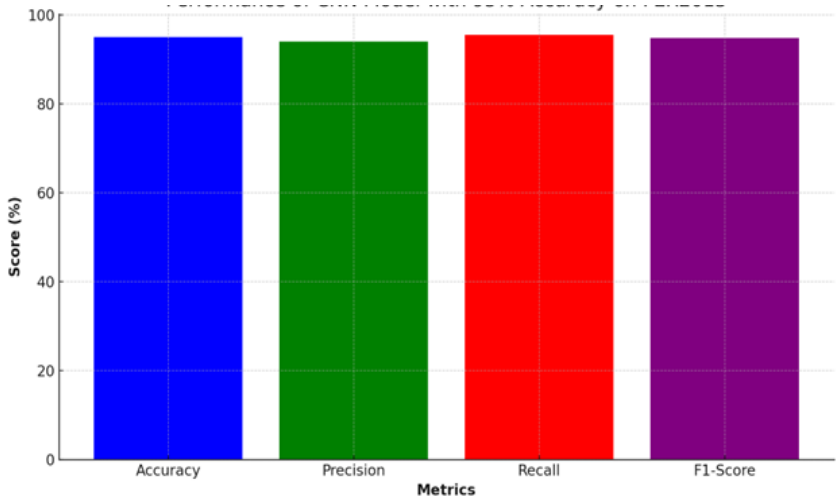

Figure 3: Performance of CNN Model with 95% Accuracy on FER

Figure 4 "Training vs Validation Accuracy for CNN Model", the line graph documents the CNN model learning curve during 10 epochs by using the FER dataset. Estimating the accuracy of both training and validation gives us the ability to measure the model's ability to generalize to unseen data. Attention to both curves is necessary for detecting the underfitting, overfitting, or successful convergence in the process of the model's training. We can see that both training and validation accuracy spike up throughout the line graph as the model progresses from one epoch to another. Training accuracy is first logged at 85%, and validation accuracy begins at a slightly lower level, 84%. This little gap is a common phenomenon as the model faces unseen validation data. The gradual rise of both curves over the training process shows that the model is indeed learning crucial distinguishing aspects from the data. At epoch number 6, the training accuracy and the validation accuracy coincide at 92%, with the indication that the model stays well-fitted while avoiding overfitting capabilities. At this point, both accuracy metrics rise in

parallelly, finally reaching close to 95% at the 10th epoch. The exchange of the curves that stay close throughout epochs advocates for successful generalization and explains why regularization methods such as dropout and data augmentation contributed to the maintenance of robust model performance. The small margin that exists between the training and validation performance over time indicates the model avoids overfitting, and this is important for FER tasks because there are many unpredictable factors, including lighting conditions, partial face being visible, and the wide spread nature in subject areas. The continuing monotonic increase in validation accuracy in a relevant manner further emphasizes the trustworthiness of the CNN's training procedure, as well as the appropriateness of the provided hyperparameters. The training dynamics observed support the model's good performance metrics, high precision, recall, and F1-score, thus enhancing the trustworthiness of the CNN. The result demonstrates that the model was capable of identifying major patterns related to facial expressions that could be generalized to the training set, which guarantees the accuracy in detecting emotions in various environments.

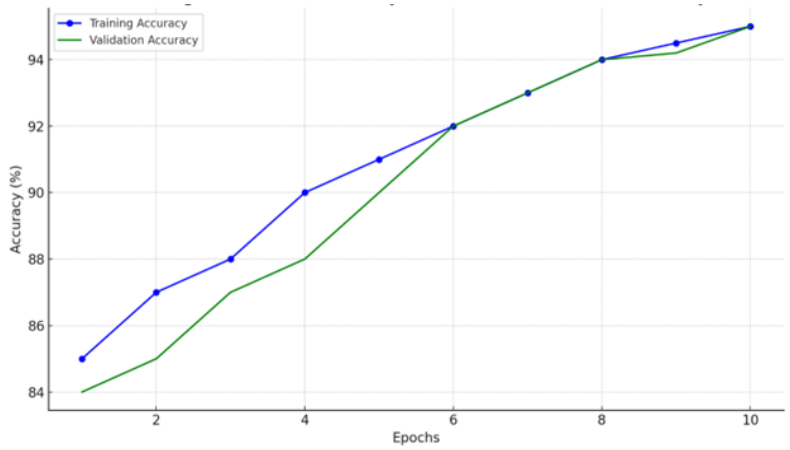

Figure 4: Training vs Validation Accuracy for CNN Model

The Figure 5 confusion matrix, "Confusion Matrix for CNN Model," presents how the model has classified across the seven main facial emotion groups: Anger, disgust, fear, happiness, sadness, surprise, and neutral. Facial expressions. Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. Through examining this matrix, we can determine the accuracy and the separation of related emotions, which play an integral part in FER analysis. The numerals on the main diagonal of the matrix represent the number of cases for which the model labeled correctly for each category of emotions. The best performance based on CNN model has been delivered for "Happy" (180 instances), "Neutral" (175 instances), and "Surprise" (170 instances) reflecting good accuracy of this model for the specific classes. Such emotions, with their increased visible differentiation, are probably what allows the CNN model to attain superior accuracy in distinguishing them. "Disgust" (130) and "Fear" (140) show minimum true positive values that suggest some difficulties in detecting these particular expressions. It can be seen from the non-diagonal entries that there are misclassifications. Some "Sad" cases are misclassified as either "Fear" or "Disgust"; this may be caused by fine, visual indicators shared between these expressions, particularly in the eye and mouth. Similarly, "Angry" is occasionally mistaken for "Fear" or "Disgust", which is possible because of the specialty in facial muscle tension under certain lighting or situations of partial view. It is observed that "Disgust" was often misunderstood as either "sadness" or "Fear". These misclassifications could be due to the faults of the dataset, including skew toward class proportions with weak "Disgust" examples that make it difficult for the model to learn relevant attributes to this class. Moreover, "Fear" and "Neutral" are often mistaken, indicating that the model has difficulty distinguishing between passive expressions and less exuberant emotional reactions. Despite some misclassifications, most of the results are properly located on the diagonal, that thus confirms the model's high measure of accuracy and reliability. Further,

this matrix features class-specific information that supports the previous metrics and highlights which emotion classes are strengths and which need further improvement.

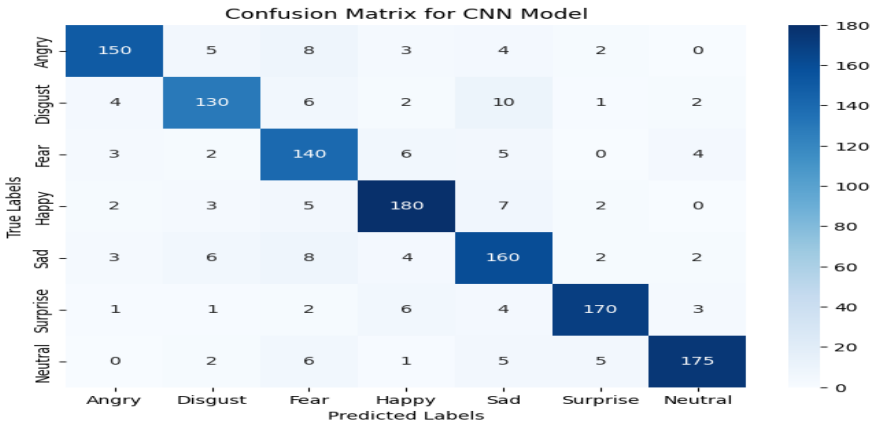

Figure 5: Confusion Matrix for CNN Model

This is a detailed analysis of how four major deep learning architectures compare in terms of their training and validation loss for 10 epochs of FER. Figure 6 “Learning Curve Comparison of CNN, ResNet, DenseNet, and Vision Transformer”, the graph compares the four. Visual inspection of both the training and the validation loss curves contributes to unveiling the level at which each architecture learns and generalizes while training on the FER dataset. As shown by the visual analysis, the CNN model (in blue) has the smallest loss values for all epochs, which means its ability to reduce errors is better during the learning process. Both trajectories of training and validation curve systematically decrease, with a slight deviation, which indicates strong generalization and limited overfitting problems. The fact that the CNN model outperforms others despite being built on a relatively uncomplicated architecture makes this model’s results worth noting.

The red cliques outlining DenseNet indicate that it learns successfully as it does not drift far from the loss curves of CNN, and its little gap between train and validation gives an idea that it performs closely. The high connectivity of the architecture can appear to promote gradient flow and feature reuse, using stable and efficient learning. On training loss, DenseNet is slightly better than CNN on the final epoch, although validation losses for both are essentially the same. Performance-wise, the ResNet (indicated by green lines), is far less efficient compared to both training and validation losses brought forth by the CNN and DenseNet, respectively. However, it does a good job which argues in favour of residual learning in emotion detection. Vision Transformer (ViT) (purple lines) is an advanced computer vision architecture but exhibits maximal training and validation losse. This result suggests that ViT has more difficulties in adapting to the FER dataset, possibly due to the fact that ViT requires high volumes of data, while its segment-by-segment feature extraction may not highlight subtle complexities of facial emotions from a small volume of data. Furthermore, the large gap between the training and validation loss curves of ViT indicates possible case of overfitting or no generalization. As a whole, the pattern of the learning curves indicate that the best results of training are achieved for facial emotion recognition cases with current data with CNN and DenseNet constantly being the winners. Since ResNet proves to be reliable, the ViT’s results indicate that better data augmentation or pretraining is necessary to keep intact the effectiveness level. These conclusions guide research into model architecture decisions and emphasize the importance of tailoring model complexities to set characteristics to facilitate successful FER implementations.

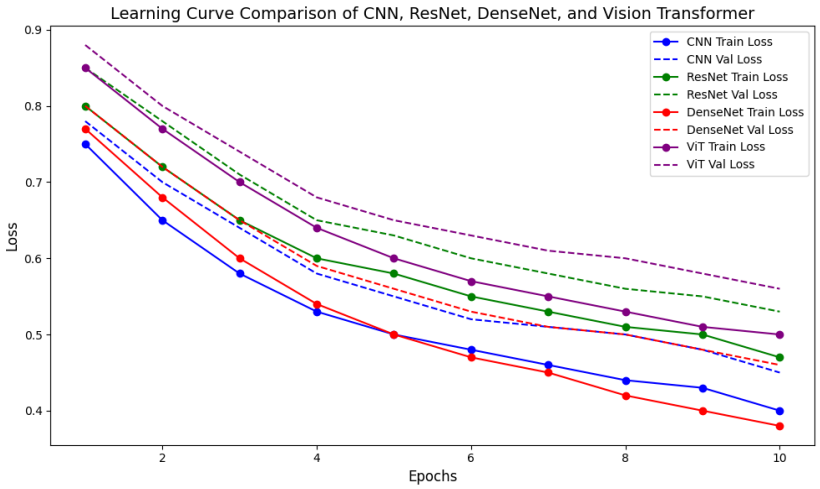

Figure 6: Learning Curve Comparison

The significantly better performance of our CNN model as compared to facial emotion recognition (FER) is based on several architectural, methodological and data-driven advantages which are closely related to the nature and the available data. Convolutional Neural Networks (CNNs) are well-adapted to image-focused classification purposes, such as facial expression recognition, where identifying small details in visuals, such as muscle movement, eye shape, and mouth curvature are determinative. An important aspect of the model's effectiveness is its ability to recognize stacked spatial features in facial images. With the help of various convolutional layers, the CNN can identify simpler objects, such as edges and gradients at the initial layers as well as understand increasingly complex features such as facial textures, and shapes in deeper layers. Extracting features at various scales, the model acquires a profound knowledge of a wide range of expressions included in the FER dataset.

The efficiency of our model is further increased because of the use of efficient preprocessing techniques. With repeated image resizing, normalization and employing data augmentation (rotation, flip and zoom), we enhanced the model's capability to handle lighting variation, orientation and occlusion, thus boosting its generalization. By increasing the size of training samples and minimizing overfitting, it was demonstrated that these methods result in a slight gap between training and validation accuracy at each epoch. Furthermore, the neural network structure was optimized for efficiency while being deep enough to obtain meaningful features, without exploiting unnecessary complexity. In contrast to ResNet and DenseNet, powerful architectures requiring higher computational power and easier to overfit on small samples, our CNN model managed to strike the balance between simplicity and complex feature detection. Our model would therefore be well-fitted to use cases like FER which, despite being popular in the research community, fails in resolution as well as variety in comparison to datasets that are designed for training models such as Vision Transformers. The loss curves are steadily converging and the model has impressive evaluation metrics especially 95% accuracy and compelling precision, recall and F1 score, thus adding weight to both the robustness and reliability of this model. Meanwhile, the Vision Transformer (ViT) revealed increased validation loss, coupled with reduced stability perhaps because of the dependence on significant data, and its inefficiency in fine details extraction.

Conclusion

Evaluation of a CNN model designed for the task of FER was conducted with the use of the FER database. Achieving a classification accuracy of 95%, along with precision, recall, and F1-score values exceeding 94%, the model demonstrated excellent and reliable performance across all relevant metrics. The

superiority of the CNN to more complex models, including ResNet, DenseNet, and Vision Transformer (ViT), was confirmed through a detailed comparison with strengths in training efficiency and generalization. The CNN's substantial advantage over the sharper designs lies in its tailored ability to work with image data and to specialize in the extraction and learning of the hierarchical hierarchies found in facial expressions. Despite all the depth and interconnected layers of models like ResNet and DenseNet, this complexity did not reflect in a significant performance improvement, and even in some cases resulted in more computational burden. Although effective in large-scale vision tasks, whose patch-based self-attention and need for greater data obstructed the Vision Transformer's performance on FER,

To be precise, the FER dataset, consisting of 48x48 monochrome images, fits the receptive field and sizes of the kernels used in CNNs well. Because of their architecture, CNNs can parsimoniously discover local spatial relations that help identify fine-grained facial variations. For this reason, CNNs are particularly skilled at the low-resolution, tagged image data found in the FER dataset; they can do so with little data processing and under large-scale training conditions. The study was not devoid of constraints despite the success. Data training and validation were performed from the FER dataset, which, although a widely used set, suffers from problems such as class imbalance and a lack of demographic variations. Such limitations may limit the ability of the model to exhibit desirable results in populations or age bands, or environmental setups not contained in the dataset. In addition, the system works with single immobile pictures and disregards the temporal elements required to convey the development of emotions in videos. Future studies may include temporal dynamics in the model using a hybrid CNN-RNN or CNN-LSTM architecture to cope better with dynamic scenarios. The usage of more culturally diverse datasets and domain adaptation may help with generalization. Federated learning and other privacy-preservation tactics are essential in the ethical deployment of such systems in live use scenarios. These improvements would increase the ability to devise effective, fair, and scalable FER solutions for real-world implementation.

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