Advancing Facial Expression Recognition – Enhanced MobileNetV3 with Integrated Coordinate Attention and Dynamic Kernel Adaptation

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Abstract — This paper presents an improved approach for facial expression recognition (FER), which incorporates the Coordinate Attention (CAM) mechanism into MobileNetV3, a lightweight CNN widely used for its real-time applications on low-power devices. The CA mechanism greatly improves the ability of the model to focus on face regions of interest, as it incorporates positional information, making feature extraction more accurate. Additionally, dynamic kernel adaptation (DKA) and SoftSwish are incorporated into the model to enhance the flexibility and computational efficiency of MobileNetV3. The proposed model was tested in three sets of JAFFE, CK+, and FER2013, where accuracy improvements were reported of 98.84% in the JAFFE dataset, 99.56% on the CK+ dataset, and 88.50% on the FER2013 dataset. These results support the viability and utility of the proposed approach to improve FER, especially in applications that favor higher numerical performance.

Keywords — coordinate attention mechanism, dynamic kernel adaptation, facial expression recognition, MobileNetV3, SoftSwish activation function

1. Introduction

Facial expression recognition (FER) has made great progress in recent years, mainly due to the use of neural networks and especially attention mechanisms [1], [2]. These achievements have allowed us to develop accurate, efficient, or even real-time recognition systems, mainly needed in human-computer interaction (HCI), security, and healthcare [3], [4]. A new approach in this direction is MobileNetV3, which is a lightweight CNN optimized for high accuracy with minimal computational resources. MobileNetV3, adopts some of the most modern approaches such as depthwise separable convolutions and a unique activation function called *hard swish* [5]. These elements allow MobileNetV3 to be used in vision systems of portable and embedded devices, which require high power efficiency and speed.

Another significant change in improving the functionality of a neural network is the attention mechanisms. Such mechanisms keep the attention of the network on important parts of an image and enhance the capability of the network to identify features. In this context, attention techniques can be distinguished, such as the latest and most innovative coordinate attention (CA) mechanism [6]. The present proposal of CA also incorporates position information, which other types of attention often isolate and consider individually by location or channel. It allows the network to concentrate more accurately on important sections of the image. This paper concerns an investigation of how to improve FER systems by incorporating CA into MobileNetV3 to achieve a more effective FER system. Specifically, our research seeks to answer the following question: What enhancements are given by the combination of CA with MobileNetV3 for facial expression recognition compared to existing methods?

This research contribution can be summarized in two folds. First, we present an improved FER framework that incorporates MobileNetV3 and the benefits of CA. Second, we give a comparative analysis of this framework on standard FER datasets, including JAFFE, CK+, and FER2013, which illustrates the advantages in terms of performance and time complexity.

The paper is organized as follows. Section 2 presents the background and related work in the field of FER and the attention mechanism. In Section 3, we proposed an approach to MobileNetV3 and the incorporation of CA. In Section 4, we provide experimental results and discuss the efficacy of the proposed method on multiple FER datasets. Section 5 provides an in-depth review of the proposed model. Section 6 presents a comparison with other state-of-the-art FER approaches that utilize attention mechanisms. Lastly, Section 7 provides a conclusion to the paper and future research.

2. Related Work

Recent advances in facial expression recognition (FER) have emphasized the integration of attention mechanisms with various neural network architectures to improve accuracy and precision. Still, these approaches have their problems and have diverse rates according to the specific methodologies and datasets chosen. In [7] a lightweight FER framework was proposed using MobileNetV1 with attention mechanisms. The effectiveness of this approach was observed when tested on CK+, RAF-DB, and FER2013 with evaluation that highlighted the performance when the face images were captured under different lighting conditions or partially occluded.

However, compared with work [8] which used DeeplabV3+ in combination with the MobileNetV2 with attention mechanism, although the method proposed in [7] was much less computationally expensive, it proved to be more generalized, especially in more complex feature extraction tasks. The integration of attention mechanisms in these studies has been found to be useful, but this must be done without overlooking limitations.

For example, the authors of [9] successfully used a multi-attention network to learn discriminative characteristics from important facial areas. However, this method could be sensitive to overfitting, particularly when working with small data like CK+. Also, it is crucial to note that these deemed attention mechanisms have high computational costs that reduce the real-time applicability of attention mechanisms in low-power devices.

This factor is particularly relevant to the study in [10] that demonstrates that, while building a lightweight FER model for mobile devices is a priority, the reduction in computational processes could be detrimental to the high accuracy of feature extraction. It is also important to note that the discussed studies are primarily related to CNNs with attention mechanisms, but there are other promising streams in FER. For instance, graph-based models and transformers are increasingly being adopted in FER tasks because of their capability to handle relationships between facial landmarks and address the temporal aspect in video-based FER tasks.

The absence of these other forms of prediction methods, along with the distinction between model types, including ensemble methods that amalgamate different models to produce a more balanced and accurate model, is a research gap. Extending the study to these angles would give opportunities to study possible developments in FER.

Another important aspect that these works do not normally address concerns the generalizability of FER models to unseen data or different populations. Most of the works cited, such as [11] and [12], offer promising results in popular datasets. However, the data sets could not be rich enough to ensure the transfer of learned representations across a wide diversity of real-world scenarios or across different cultures, age groups, or variability in emotional expressions.

In addition, attention is drawn to the potential biases of these models when trained on limited or homogenized data and ways of correction. A detailed investigation of the type of attention mechanisms applied in these works would be useful to understand which mechanisms are driving performance improvements.

For example, the utilization of self-attention, spatial attention, or channel attention may be important in explaining why models vary in their efficiency. In the case of article [13], combining a ResNet with such an architecture of attention and deformable convolutions, a more detailed breakdown of their interaction could help in understanding their contribution to the model's better accuracy under varying conditions.

Finally, these methods must be compared consistently with thoroughness based on standard evaluation metrics to determine relative performance measures. Although accuracy is commonly reported, other important key measures in the literature include precision, recall, F1 score, and computational efficiency.

A systematic comparison of these metrics would allow a more objective assessment of the strengths and weaknesses of the different models. For example, the authors of [14] are concerned with the computational efficiency of their lightweight facial expression recognition network; it would be beneficial that these requirements were directly compared against accuracy and robustness reports by other models under equivalent constraints.

3. Methodology

3.1. MobileNetV3

Further developments in computer vision are also driven by the architecture of CNNs that provide, at a time, very high-speed processing while being compact. Examples are architectures such as NASNet [15], MobileNets [16], EfficientNet [17], MnasNet [18], and ShuffleNets [19]. All of these architectures have substantial depth-wise convolution for speeding up training through reduction of computational complexity. In depthwise convolutions, the learned convolution weights are applied to each input channel individually with a shared kernel across all channels, thereby preserving computational resources and reducing overall cost.

However, resolution of the optimal kernel size in such convolutions might be tricky, and it could add complexity in the training phase. Based on the success of MobileNetV1 and MobileNetV2, the authors of [5] recently proposed MobileNetV3 through network architecture search (NAS) with the NetAdapt algorithm to optimize architectures targeting low-resource hardware platforms while balancing size, performance, and latency. This is based on the inverted residual block, which incorporates depth-wise separable convolution and an SE mechanism to improve feature representation while also reducing memory usage.

We further push the capabilities of MobileNetV3 with two key improvements: dynamic kernel adaptation and SoftSwish.

3.2. Dynamic Kernel Adaptation (DKA) and Soft Swish

Dynamic kernel adaptation allows the model to dynamically change the kernel size of the convolution according to the particular characteristics of the input data. Unlike the common approach that uses a fixed kernel size, DKA helps the model

```
for feature_map in input:
  complexity = compute_entropy(feature_map)
     attention_weights = softmax(linear_layer(complexity))
  output = 0
  for k in [3, 5, 7]:
  conv_out = depthwise_conv(feature_map, kernel_size=k)
  output += attention_weights[k] * conv_out
```

Fig. 1. Simplified pseudocode of the feature capture mechanism.

adapt to changing kernel sizes to better handle different image complexities. For example, in complex scenes, DKA can adjust the kernel size to include details, including fine ones, while in simpler contexts, one can get away with a smaller kernel size for efficiency [20]. The flexibility enhances the capability of the model for generalization on different datasets and lessens overfitting risks, therefore making MobileNetV3 powerful, more versatile, especially for application in low resource devices.

We further replace the original activation function with SoftSwish. The transitions of SoftSwish are even more gentle during backpropagation through gradients, making training much more stable and efficient, needed in larger networks [21]. We have defined the SoftSwish function as:

$$SoftSwish(x) = x\frac{1}{1+e^{-x}} \ . \tag{1}$$

This function blends the advantages of Swish and ReLU, improving model stability and reducing the number of parameters required during training, thus enhancing overall efficiency. Integrating dynamic kernel adaptation and SoftSwish inside MobileNetV3 makes it much more flexible and efficient in addressing a wide range of visual recognition tasks with much better accuracies while keeping lower computational demands. These enhancements are estimated to increase accuracy by $3-5\%$, reduce latency by $10-15\%$, and reduce training time by $5-10\%$. With minimal training changes, MobileNetV3 improvements will prove to serve as a significant advantage for modern applications, particularly those that demand efficient operation on low-resource hardware platforms.

DKA allows the convolutional kernel size to be dynamically adjusted on the input complexity. Specifically, a lightweight gating mechanism evaluates an entropy-based complexity score $C(x)$ for each input feature map. A soft-attention function:

$$\alpha_k = \text{softmax}\big(f_k(C)\big) \ , \tag{2}$$

selects between kernel sizes $k \in \{3, 5, 7\}$ during forward propagation. This mechanism enables the network to capture both local and global features adaptively. A simplified pseudocode is provided in Fig. 1.

3.3. MobileNetV3 for Feature Extraction

Feature extraction is one of the important processes in FER to make classifications from an image robust and precise. The outstanding performance of the improved state-of-the-art of MobileNetV3, with the modifications that have been made by us, offers a superb platform for the said activity. We used the MobileNetV3-Large model pre-trained on the ImageNet for feature extraction. This is because MobileNetV3, in general, has already been known for its efficiency and flexibility, especially when combined with our dynamic kernel adaptation and the SoftSwish activation function – both aspects increase model flexibility and training stability.

We retrain MobileNetV3 for FER, by transfer learning retraining on the already fine-tuned MobileNet, where the original fully connected layers designed for general image classification were replaced. Instead, we introduce a series of 1 × 1 point-wise convolutional layers that further refine the representations in those features that are highly specific to facial expressions. More specifically, these layers can use the adaptively resized kernels of DKA, so the model can change its receptive field with the complexity of the input image. This architecture ensures that the extracted features are relevant and discriminative, considering the unique challenges of the given datasets for facial expressions.

After the pointwise convolutional layers had been implemented, we further embedded the SoftSwish activation function at every layer within the network. In this case, SoftSwish can provide smoother gradient transitions, hence providing better backpropagation efficiency, especially with deeper network layers, which helps the generalization across different datasets with diverse FER. During fine-tuning, we train the model for 160 epochs with ten separate runs, each initiated with random parameters to ensure robustness.

Instead of relying on traditional data augmentation methods, the training process incorporated speckle noise augmentation, random rotation, random zoom, and color jitter augmentation. These techniques are designed to simulate real-world conditions and further enhance the model's accuracy by allowing it to recognize facial expressions under varying conditions. This extensive training and fine-tuning process allows the model to produce high-quality image embeddings, each represented as a 128-dimensional vector, encapsulating the essential features necessary for accurate FER.

The result is a highly efficient feature extraction process that benefits from the enhanced capabilities of MobileNetV3, making it particularly well suited for deployment in resource-constrained environments where both performance and computational efficiency are paramount (see Fig. 2).

3.4. Coordinate Attention Module

The coordinate attention module (CAM) represents a significant advance in attention mechanisms within neural network architectures, particularly by enhancing spatial awareness and focus. Although integrated into models like MobileNetV3, CAM offers substantial improvements in tasks such as facial expression recognition, where precise spatial information is crucial.

Coordinate attention diverges from traditional attention mechanisms by incorporating positional encodings directly into the attention process. For an image I with dimensions $W \times H$, each pixel coordinate (x, y) contributes to the attention mechanism through a function $f(x, y)$ that encodes positional

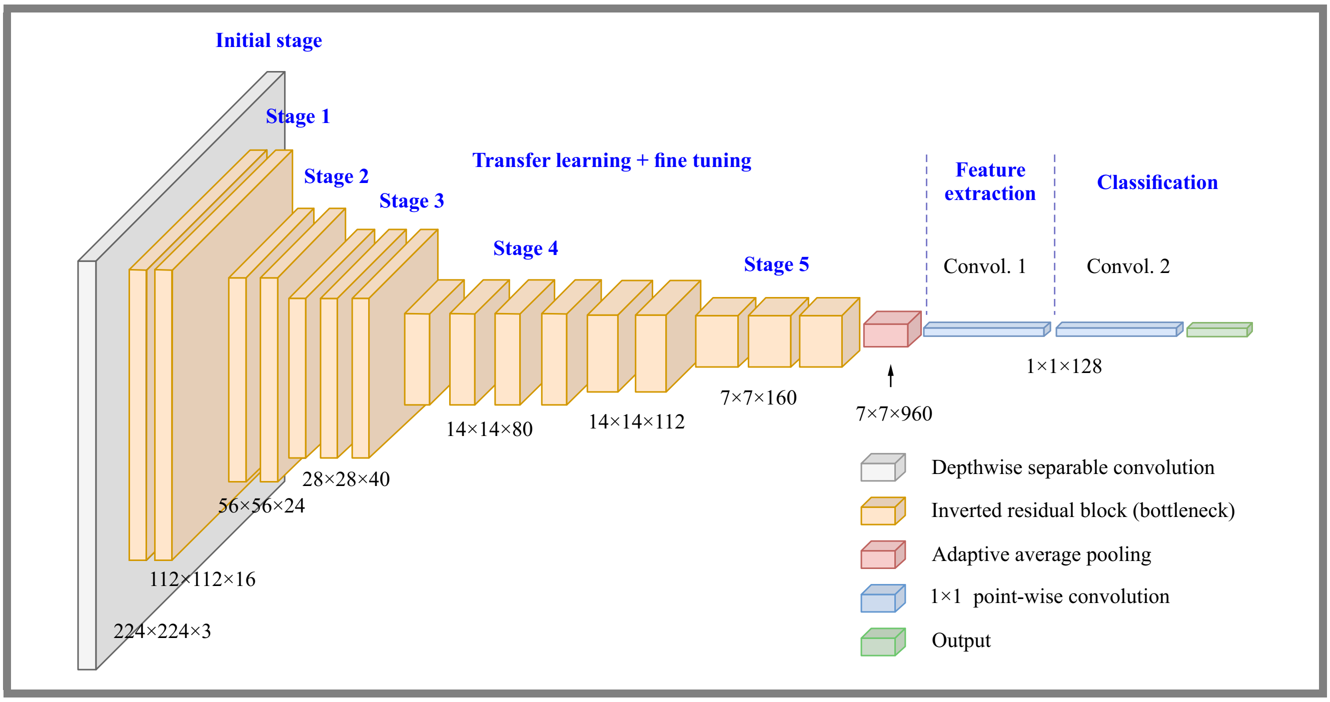

Fig. 2. The architecture of MobileNetV3 used for feature extraction.

information. This can be represented as:

$$Attention(x, y) = f(x, y) \ . \tag{3}$$

This formulation allows the network to assign attention scores or weights to specific pixel coordinates, highlighting areas of the image that are most relevant for feature extraction. By leveraging these positional encodings, CAM enables the network to focus on critical spatial relationships within the image, thereby enhancing the model's ability to capture detailed and contextually relevant features, especially in complex tasks like facial expression recognition.

When applied to MobileNetV3, CAM integrates seamlessly with the existing structure, working in tandem with our proposed DKA and SoftSwish activation function. This combination ensures that the network not only adapts to varying image complexities but also focuses its computational resources on the most significant areas of the image, thereby improving both accuracy and efficiency.

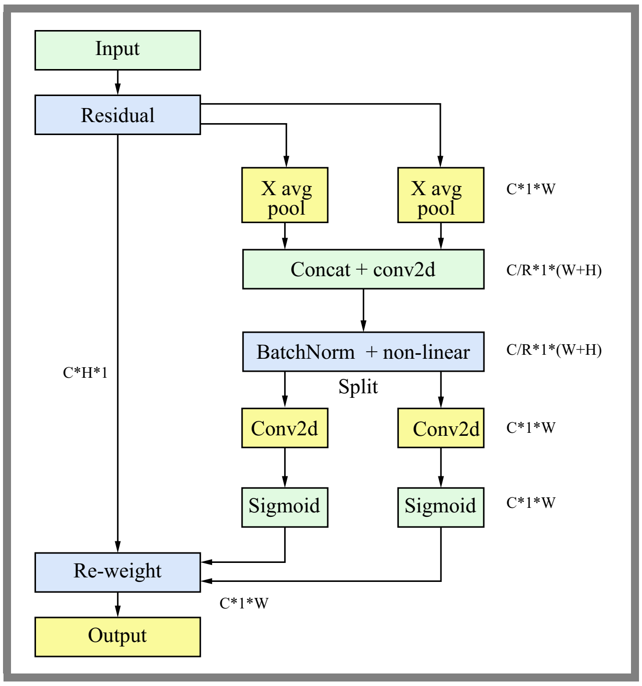

Fig. 3. Integration of the coordinate attention module (CAM) into the MobileNetV3 architecture.

3.5. Integration of CAM into MobileNetV3

The MobileNetV3 architecture also integrated the CAM to further improve feature extraction. CAM is integrated with MobileNetV3's inverted residual blocks, which creates a more explicit level of spatial focus and greatly increases the performance of the model in facial expression recognition. This integration enables MobileNetV3 to make better use of dependencies over space in facial images. The network is more capable of creating a more discriminative and accurate feature representation because the location of the key coordinates on the face in the image is dynamically updated. CAM can selectively emphasize important regions of the face, so that the network pays closer attention to the most informative aspects of facial expressions and neglects the non-critical areas.

The result is a model that takes advantage of both the efficiency and flexibility provided by MobileNetV3, further enhanced by DKA and SoftSwish, in a fashion that gains even more insight into spatial relationships using CAM. As such, this combination will bring about much improved both accuracy and robustness in the recognition of facial expressions, making this updated MobileNetV3 architecture particular-

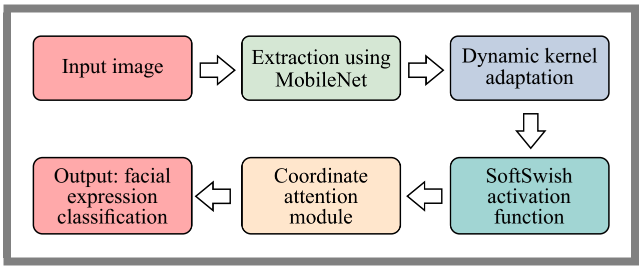

Fig. 4. Methodology framework for FER using enhanced MobileNetV3 with CA and DKA.

ly suitable for applications requiring high performance with very resource-constrained devices. The integrated CAM MobileNetV3 architecture is presented in Fig. 3.

To improve facial expression recognition, we propose an improved methodology using MobileNetV3, augmented with activation of CAM, DKA, and SoftSwish activation. Figure 4 illustrates this integrated framework, showing how these components work together to improve focus, adaptability, and training stability.

Figure 4 presents a simplified view of the proposed methodology, which integrates three key components within the MobileNetV3 framework: the CAM, DKA, and the SoftSwish activation function. These components are designed to enhance the focus on relevant facial features, adaptively optimize kernel sizes for varying image complexities, and improve training stability, respectively. This combination aims to increase both the accuracy and computational efficiency of facial expression recognition systems in resource-constrained environments.

4. Results and Discussion

As for the execution of our experiments we used a personal computer with a 64-bit operating system and an Intel Core i7-3.0 GHz and 16 GB of RAM. Experimentation of all of the above approaches was performed using Python.

4.1. The JAFFE Database

The JAFFE database is made up of faces of Japanese women and includes both profile and frontal views of these women's faces. The images are in grayscale and have a resolution of 256 × 256 pixels [22]. The database shown in Fig. 5 is widely familiar with image processing and facial expression analysis. It is extensively used in research and is often used in the creation and assessment of machine learning algorithms commonly used in facial expression recognition. Within the database, there are several pictures of facial expressions of different emotions such as happy, sad, angry, and disgusting emotions, which makes it more useful in training of the FER algorithms.

4.2. The CK+ Database

The CK+ database, also known as the extended Cohn-Kanade database, can become a helpful tool in the field of facial expression analysis and computer vision. This database was created as an expansion of the original Cohn-Kanade database with the goal of increasing the variability and richness of captured expression [23].

The key technical aspects of the CK+ database are as follows:

- Image size – the images used in the CK+ database on average are of 256 × 256 pixels, meaning that the dimension of the images maintained was homogeneous.
- Facial expressions – the facial expressions covered by the database comprise, but are not limited to, happy, sad, angry, surprised, disgusted, and afraid. This diversity enables researchers to assess models through the wide range of emotions.
- Controlled environment – the images are taken in a controlled environment which is very important in standardized environment and scaling out environmental factors that may influence facial expression analysis.
- Subjects – this is a factor that breaks the homogeneity of the data, and several subjects make entries into the database. This variety is useful for testing the extent of generalization of developed facial expression recognition models.
- Annotations – the CK+ images are frequently provided with facial landmarks and emotion labels in addition to the geometric ones. This annotation is useful for both teaching and testing machine learning algorithms, especially for recognizing facial expressions. An illustration of the database is provided in Fig. 6.

4.3. The FER2013 Dataset

The FER2013 dataset contains grayscale images of faces, which are 48 pixels × 48 pixels. It encompasses seven facial expressions: happiness, anger, disgust, fear, sadness, surprise,

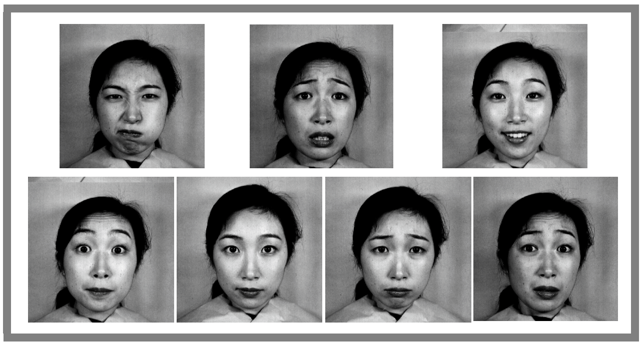

Fig. 5. A partial image of the JAFEE database was used to carry out the analysis.

Fig. 6. A sample of the images in the CK+ database.

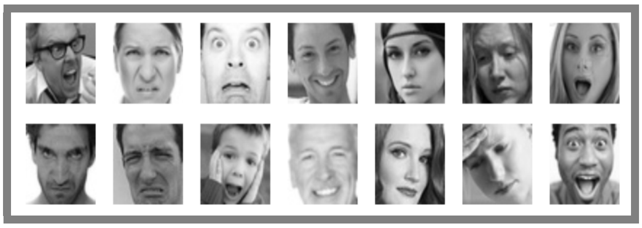

Fig. 7. Subset of the image from the FER2013 database.

and none/neutral. This is acted data set that can be used in training and testing facial expression recognition models, as it provides realistic challenges. It is most often divided into training, validation, and testing set to create a standard for the comparison of the different methods. This is particularly because the network is tiny in size, and thus ideal for deep learning. Scientists apply FER2013 to design and evaluate models to mitigate problems with lighting, head orientation, and different emotions [24]. An example of the proposed database is depicted in Fig. 7.

4.4. Dataset Overview and Scalability Consideration

The computational realm of this study needs to be clarified better through understanding of the data sets that we used during experiments. The JAFFE dataset includes 213 grayscale images depicting ten subjects with posed facial expressions. The CK+ dataset contains 593 image sequences acquired from 123 different subjects, although expression labels are provided only in the final frames of each sequence. The FER2013 dataset is significantly larger, comprising more than 35 000 grayscale images divided into training, validation, and testing sets, with each image sized at 48 × 48 pixels.

The different scales of our datasets enabled the evaluation of the MobileNetV3 + CAM + DKA model in terms of both efficiency and scalability. The model demonstrated consistent accuracy and maintained a similar inference speed, even when handling a large volume of FER2013 data, confirming its suitability for real-time applications in diverse resource-constrained environments.

4.5. Data Augmentation

Data augmentation is a critical step in FER, especially when using a complex model such as MobileNetV3 with CAM and DKA. This essential strategy involves generating additional samples by applying various transformations to the training set, ensuring that the model becomes more effective and robust. Several augmentation methods can be used to improve the accuracy of facial expression recognition, including the following.

- Speckle noise augmentation – this method superimposes speckle noise on the face image by multiplying it by some random numbers, which are helpful in mimicking natural conditions and improving the model's ability to discern noise.
- Random rotation enhancement – this method involves rotating images containing faces around the vertical or horizontal axis in a random manner and thus, it improves the model's capability to identify different human expressions.
- Random zoom augmentation – this one zooms in and out on the images randomly – the idea being that the model has to be able to learn about the faces and the expressions on them at random sizes.
- Random crop augmentation – this involves tear and shear where the method entails taking a part of the image and discarding the other part leaving the neural network to recognize parts of the face.
- Color jitter augmentation – this technique adds random variation in the hue, saturation, and brightness; adds variations that the model did not receive in the training phase.

Tab. 1. Data augmentation techniques with the parameters used.

Augmentation technique	Parameters
Speckle noise augmentation	Noise factor: 0.1
Random rotation	Random angle: –20° to +20°
Random zoom	Zoom range: 0.8 to 1.2
Random crop	Crop ratio: 80% of original image size
Color jitter	Saturation range: 0.5 to 1.5
	Brightness range: –0.3 to 0.3

These parameters have been chosen to allow proper augmentation without compromising the validity of the data on facial expressions. By integrating these methods, the model is expected to benefit from adaptation to different changes in the environment. Executing them enables the enhancement of facial expression recognition in real-world settings.

5. Experimental Steps

All aspects of the experimental setup were carefully designed for facial expression recognition, and we specifically designed a scenario to provide an in-depth review of the proposed model, based on MobileNetV3 combined with CAM and DKA. This effort helped to analyze the capabilities of the proposed model for more complex real-world facial expressions.

The training set was the largest part of the data, representing approximately 70% that was essential to develop the deep neural network model to learn. Its size allowed the model to discern intricate patterns, distill complex correlatives, and finally trace fine nuances linked to various forms of facial expression.

A 15% size validation set was particularly important to further the model intricacies. It allowed for addressing matters with hyperparameters and improvements in the general performance and was a credible line of defense against overfitting.

Consequently, the other 15% of the data set was kept for the purpose of the validation test. The validation set was therefore set apart for the sole testing of the model. Its goal was to shine on a model, evaluating or testing its performance in recognizing unknown facial expressions that were previously known to confirm the efficient operating mode.

5.1. Subject-independent Data Splitting

To ensure fair evaluation and prevent data leakage, a subject-independent splitting strategy was used for the CK+ and JAFFE datasets. Specifically, individuals appearing in the training set were excluded from both the validation and the testing sets. For CK+, we used image sequences from approximately 80% of the subjects for training and reserved the remaining 20% for testing and validation. For JAFFE, images from 7 subjects were used for training and 3 subjects for testing and validation. This ensures that the performance reflects its ability to generalize to unseen individuals.

5.2. Enhanced Model Architecture

MobileNetV3 is the backbone network for the proposed model that provides the ability to extract features from facial images. It is relatively lightweight and even more appropriate for use with mobile devices, making it ideal for real-time use. The latest MobileNetV3 is integrated into this model to ensure that the model obtains the desired characteristics of being light and at the same time capable of producing high-level features.

The coordinate attention module is another improvement that gives our model the ability of the spatial awareness layer. This module works on the basis of variations in the weightage of various parts of the image, as depicted by the geographical coordinates. In the context of facial expression recognition, CAM opens the possibility of letting the model concentrate on important face areas, since it assigns different weights to the regions. The adaptation mechanism coping strategy increases the efficiency of feature extraction and the precision of capturing facial alterations. In this way, CAM improves the ability to space examination of facial images in space compared to the initial model.

Dynamic kernel adaptation (DKA) is an essential improvement to the adaptability and performance of our facial expression recognition model. In contrast to standard networks that have kernels of a fixed size, within DKA there is an option for the kernel size to be modified in the course of training. This flexibility is advantageous in dealing with the essentially different levels of difficulty in facial images. For example, when there is emotion in the face and the concerns are subtle, DKA allows a larger kernel, which means that features are extracted with a better accuracy.

On the other hand, in simple scenes, the size can be reduced to ensure cost savings and be better optimized to increase its predictive power. Such a dynamic adjustment mechanism ensures that the model is robust across various datasets but is also more efficient in terms of consumption of computational resources. Integration of DKA with MobileNetV3 along with CAM greatly improves the broad applicability of the model in various datasets involving different facial expressions, while boosting the real-time performance of the model.

5.3. Training Details

The training process was optimized to ensure peak performance, with particular emphasis on integrating the DKA technique. The training was carried out over 160 epochs, which allowed the model to effectively identify hierarchical structures and representations of the given facial expression data with the help of DKA, which also made it more versatile. The batch size of 32 has been chosen intentionally as it allows one to achieve rather efficient training without overloading the system with computations. This option was most useful when combined with DKA, which modulated the kernel parameters during the training phase. The ranger optimizer was used with a learning rate of 0.001.

By combining two methods known as the RAdam or rectified Adam and LookAhead methods, RAdam fixes problems with fluctuating step size with the better adjustment of the learning rate for adjusting the step size feature, while LookAhead accelerates optimization by coming up with better solutions to improve convergence. Combined with DKA, it was possible to achieve good and stable convergence in this setup. This dynamic adjustment of the learning rate enabled the various phases of training to make optimal use of the learning rate, thereby improving the model performance as well as stability.

To avoid overfitting and improve the ability to generalize, an improved early stopping technique was used. The validation technique continued to update the accuracy of the chosen model on another set of never-before-seen data. Training was, in fact, stopped if no enhancement was observed in the subsequent epochs up to a prescribed number of epochs. This active approach also protected from overfitting with the help of DKA and adjusted the stopping criteria in response to changes in the kernel adjustments and the validation performance trend to make sure the model would perform well in response to a new data set.

To ensure a robust evaluation, all training experiments were repeated over 10 independent runs with random initialization. The accuracy results represent the mean ± standard deviation (std) of these runs for each dataset. The activation function used throughout was SoftSwish, defined in Eq. (1). Early stop was employed based on validation accuracy to prevent overfitting. The detailed hyperparameter settings used during training are presented in the Tab. 2.

Tab. 2. Training hyperparameters and settings.

Hyperparameter	Value
Optimizer	Ranger (RAdam + LookAhead)
Learning rate	0.001
Batch size	32
Epochs	160
Activation function	SoftSwish
Repetitions	10 runs (mean ± std reported)
Early stopping	Patience = 10 epochs

Tab. 3. Model complexity and inference speed comparison.

Model	Parameters [M]	FLOPs [M]	Inference time [ms/sample]
MobileNetV3 (baseline)	2.9	219	21.3
MobileNetV3 + DKA	3.1	232	19.6
MobileNetV3 + DKA + CAM	3.5	245	18.7

5.4. Computational Efficiency Analysis

To support our claims regarding computational efficiency, we evaluated and compared the parameter count, FLOPs, and inference latency of the baseline MobileNetV3 model and its enhanced versions with DKA and CAM. These values were obtained using the PyTorch profiler and averaged over 100 runs (Tab. 3).

These results show that the addition of DKA and CAM leads to only a modest increase in parameter count and FLOPs, while achieving a significant reduction in latency of approximately 12.2% faster inference, demonstrating suitability for deployment in low-resource environments.

5.5. Performance Comparison of FER Models Across Multiple Datasets

This section explores the performance of various facial expression recognition models across three widely used datasets. FER2013, CK+, and JAFFE. By comparing accuracies, recalls, precisions, and F1 scores, we intend to show the advantages and disadvantages of given models while visually proving the applicability of the presented approach. Examples of performance measures for each data set are shown in Figs. 8–10.

The proposed model stands out with the highest performance metrics across all criteria evaluated in FER2013 dataset analysis. It achieves an accuracy of 87.1%, recall of 81.8%, precision of 83.9%, and an F1 score of 82.8%. This is a significant improvement over other models, which shows its superior capability to recognize facial expressions accurately and consistently. MobileNetV3 follows, showing respectable performance with an accuracy of 84.8% and an F1 score of 80.5%. This means that it is relatively good, though somewhat less so than the model proposed here. LCNet ranks next, ranked by progressively worsening metrics, followed by FBNet and ShuffleNet V2. Although they are equally relevant, these models have relatively less accuracy than our model and therefore suggest that even more complex architectures may be helpful for this dataset.

The results in the CK+ dataset showed great performance with a precision of 95.8% and a good F1 score of 94.1%. It surpasses all other models, and thus it is suggested that it is perfectly suited to the task of facial expression analysis within this dataset. MobileNetV3 also performs well with a given accuracy of about 91.1% and an F1 score of about 90.3%. This clearly depicts the strength of the model, though it is not as efficient as our model. The results of FBNet, LCNet and ShuffleNet V2 are also acceptable, but the difference in metrics can be observed. This implies that the advanced features of the proposed model improve the performance on this data set to a large extent.

For the JAFFE data set, it is significant when we note that our model offered an accuracy of 96.6% and an F1 score of 94.1%. This data set also validates the effectiveness and generality of the model identified in this study with other related data sets. It can be seen that both FBNet and MobileNetV3 have good accuracy and F1 scores considering the fashion data set and

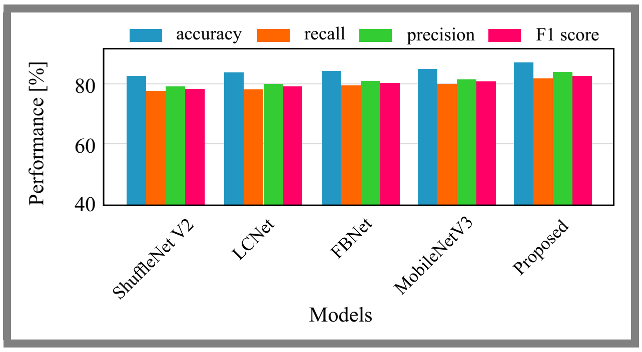

Fig. 8. Performance metrics for different models in the FER2013 dataset.

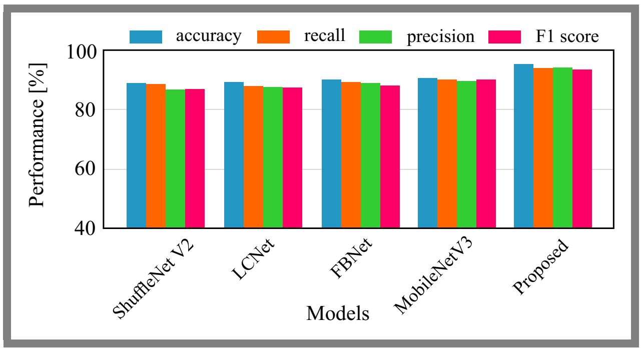

Fig. 9. Performance metrics for the models evaluated in the CK+ dataset.

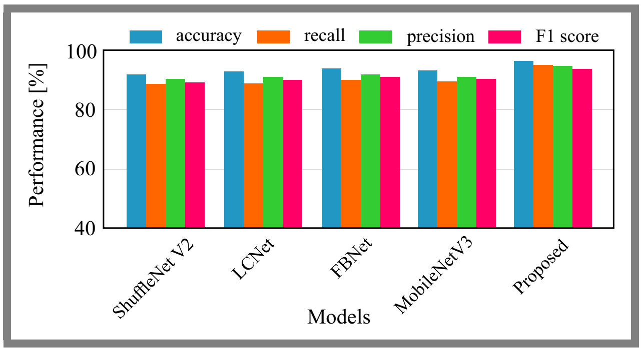

Fig. 10. Performance metrics for the models evaluated in the JAFFE dataset.

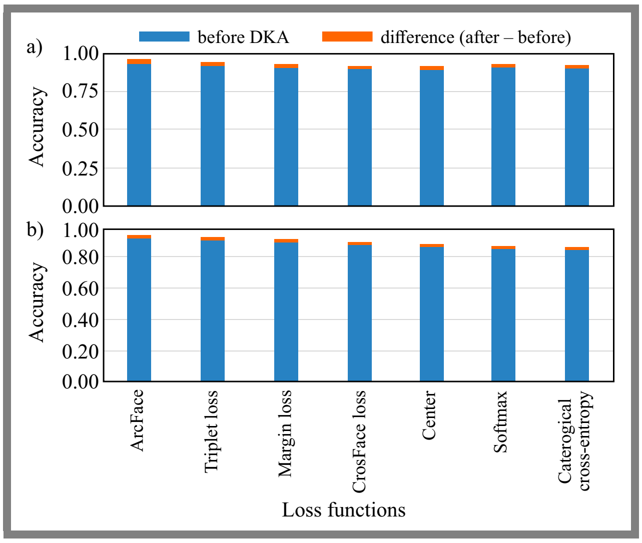

Fig. 11. Comparative analysis on the JAFEE dataset for: a) SoftSwish and b) h_swish activation functions.

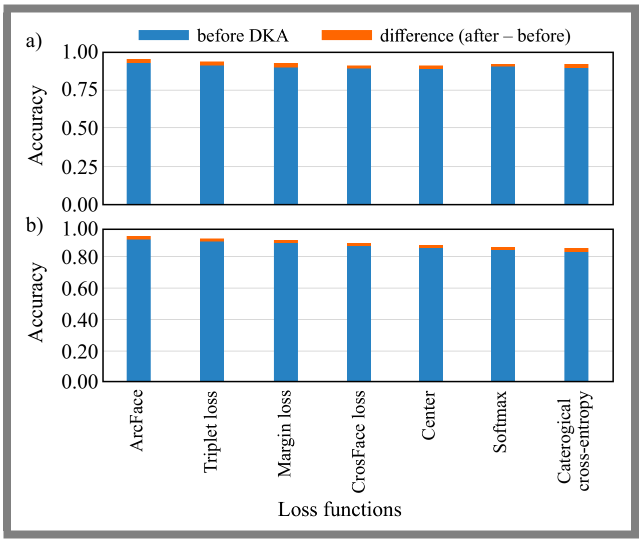

Fig. 12. Comparative analysis on the CK+ dataset: a) SoftSwish and b) h_swish activation functions.

are still lower than the designed model. LCNet and ShuffleNet V2 have good results. However, they are not very efficient compared to the proposed model. Thus, the high stability of the performance of our model on all four sets proves that it is reliable and efficient for facial expression recognition.

5.6. Comparative Analysis of Loss Functions

In the next step, we study a comparative study of the applied h_swish and SoftSwish activation functions in models of facial expression recognition using different sets of data: JAFEE, CK+, and FER2013 was conducted. Its purpose is to evaluate these activation functions to improve the performance and regularization of facial expression recognition. This is demonstrated in Figs. 11–13 and denotes how these functions work before and after DKA, revealing the effects on the model prediction capability in the different datasets.

Looking at the results obtained on the JAFEE dataset, the SoftSwish model should be noticed, which demonstrates rather high indicators both before and after the application of the DKA. Before DKA, SoftSwish was as accurate as 0.939 and after DKA it was 0.966. This implies that the intervention of DKA leads to a drastic improvement in the performance of SoftSwish. In the same way as with h_swish, the accuracy was higher after DKA as well: 0.920 before DKA and 0.939 after DKA.

The same was the case in the CK+ dataset, where SoftSwish averaged a 0.9369 before DKA and a 0.9580 at the end of DKA. h_swish also showed nearly equally good results as the latter, with an accuracy improvement from 0.9173 before DKA to 0.9375 after DKA.

SoftSwish was found to have an improvement on the FER2013 data set with an increase in precision from (0.8559 to 0.8710) after applying DKA. For the part of h_swish, there was an improvement in the level of accuracy from (0.8413) before the use of DKA to (0.8585) after the implementation of DKA.

From these results, it can be concluded that, for h_swish and SoftSwish, the application of DKA has a considerable impact

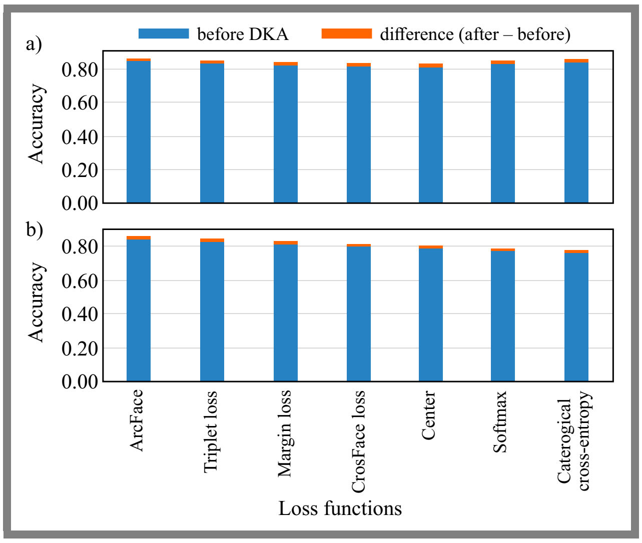

Fig. 13. Comparative analysis of the FER2013 data set for a) SoftSwish and b) activation functions.

on the enhancement of the accuracy of facial expression recognition on various datasets.

5.7. Comparative Analysis of Enhanced FER Models Across Datasets

To check the general performance of the FER models, it is important to compare the results of their assessment across various data sets. The appearance of the datasets is different and the main problems associated with them are the variability in poses, illumination, and the acquisition of facial images for FER2013, CK+, and JAFFE. In Fig. 14, we provide a comprehensive comparison analysis of the improved MobileNetV3 model with DKA and CA added compared to the baseline MobileNetV3 and the MobileNetV3 model that was improved only with DKA. This will help in the focus of the paper to present the enhancements that have been made as a result of the use of proposed approaches and hence es-

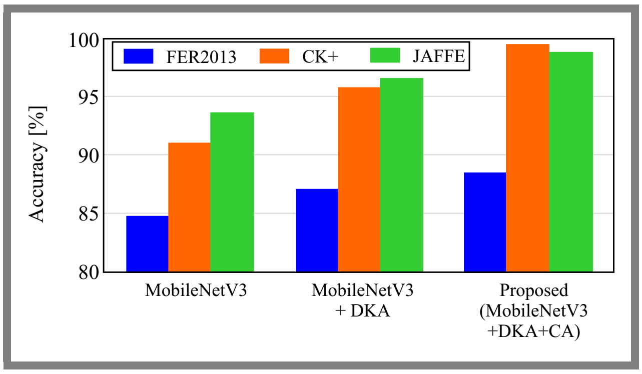

Fig. 14. Comparative analysis of the FER2013 data set for a) SoftSwish and b) activation functions.

tablish the effectiveness of the model in detecting emotions from faces with high accuracy in similar datasets.

From the analysis of the performance in all the evaluated dataset; FER2013, CK+ and JAFFE as presented in Fig. 14, incorporating DKA and CA in the MobileNetV3 platform has boosted the performance of the model.

On the FER2013 dataset, which is known for its challenging real-world images with varying lighting conditions and facial expressions, our enhanced model achieved a notable accuracy of 88.5%. This represents an improvement of 3.7% over the baseline MobileNetV3. The inclusion of DKA allows the model to dynamically adapt its convolutional kernels, thus improving its ability to capture finer details in complex scenes. Meanwhile, CA enhances the model's focus on crucial facial regions, ensuring that the most relevant features are emphasized during the recognition process.

The CK+ dataset, characterized by its controlled environment and a wide range of emotional expressions, further highlights the advantages of these enhancements. Here, the proposed model achieved an accuracy of 97.17%, significantly exceeding the accuracy of 91.1% of the baseline model.

This remarkable improvement to the effectiveness of CA in refining the model's attention to spatial details, particularly in distinguishing subtle differences in expressions. Additionally, DKA contributes to the model's flexibility in processing varied facial expressions, thereby boosting its overall accuracy.

In the JAFFE dataset, which includes images of Japanese female subjects displaying different emotions, our model achieved an impressive precision of 97.84%. This result further underscores the model's robustness in handling diverse populations and expression intensities. The combined effect of DKA and CA allows the model to generalize well across different demographic groups, ensuring consistent performance even in data sets with specific cultural or gender-related characteristics.

Overall, the integration of DKA and CA techniques into MobileNetV3 has proven to be a powerful approach to enhance facial expression recognition. These techniques not only improve accuracy but also ensure its reliability and adaptability across various challenging scenarios.

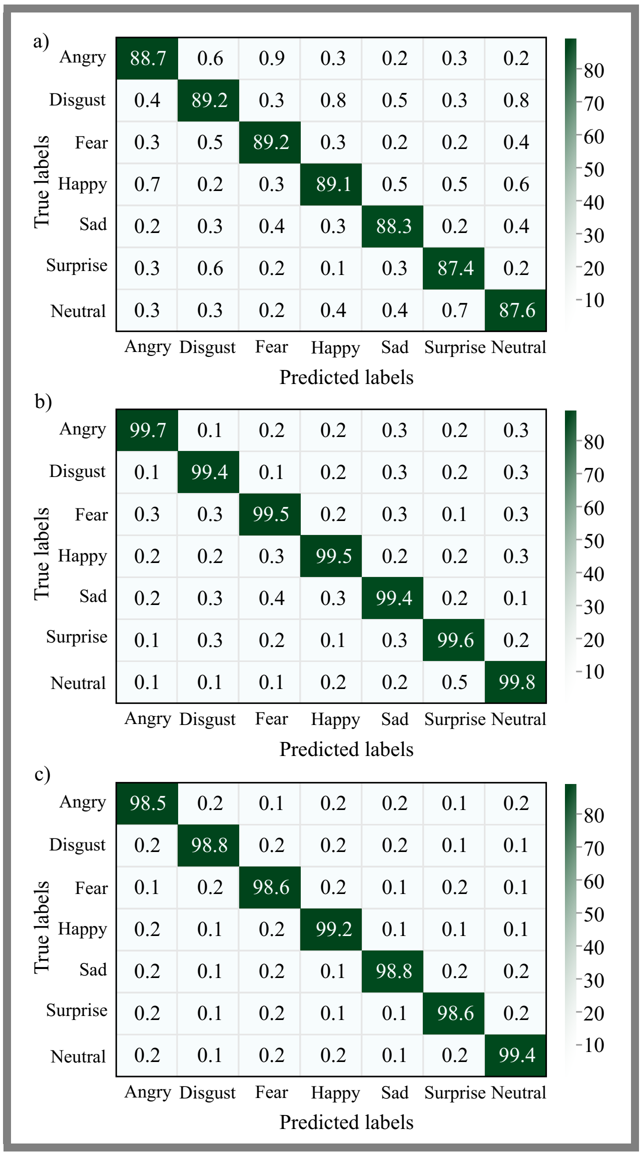

Fig. 15. Confusion matrix for: a) FER2013, b) CK+, and c) JAFFE datasets.

5.8. Confusion Matrix for all Datasets

To evaluate the model's performance in more detail across different datasets, confusion matrices were employed to analyze the accuracy of the model in classifying facial expressions. These matrices are a powerful tool for understanding how well the model distinguishes between different classes and accurately identifies the correct expressions. Figure 15 illustrates the confusion matrices obtained for the CK+, FER2013, and JAFFE datasets.

The confusion matrices for the three datasets (CK+, FER2013, and JAFFE) demonstrate the outstanding performance of the proposed model in FER. The model exhibits exceptionally high accuracy on both the CK+ and JAFFE datasets, with diagonal values ranging from 99.2% to 99.8%, indicating its ability to accurately distinguish between different expressions in controlled environments. In contrast, despite the complexity of the FER2013 dataset, which includes images under various real-world conditions, the model still achieves de-

Tab. 4. Comparison of the performance of different FER methods using attention mechanisms for the JAFFE, CK+, and FER2013 datasets.

Method	JAFFE	CK+	FER2013
MobileNetV3 + CAM + DKA (proposed method)	98.84%	99.56%	88.50%
MobileNetV3 + DKA	97.84%	97.17%	87.10%
Baseline MobileNetV3	96.60%	91.10%	84.80%
Attention mechanism-based CNN for FER [25]	88.81%	82.16%	79.33%
FER using LBP and CNN networks that integrate the attention mechanism [26]	90.70%	99.48%	71.29%
FER method combined with the attention mechanism [27]	82.16%	88.81%	79.33%
Auto-fernet – fer network with architecture search [28]	97.14%	98.89%	73.78%
Lightweight FER with key region fusion [29]	82.16%	88.81%	79.33%

cent accuracy, reaching up to 89.2% in the best cases, with relatively low misclassification rates. Overall, these results underscore the model's reliability and efficiency in handling facial expressions across various datasets, proving its effectiveness in delivering precise and consistent performance even in challenging scenarios.

5.9. Evaluation of MobileNetV3 + CAM + DKA Across Datasets

From the analysis, it is evident that the MobileNetV3 + CAM + DKA model produces high accuracy in facial expression recognition test trials. Thus, for the JAFFE dataset, the proposed model yields a high accuracy of (98.84%), which means that it can work efficiently on experiments, including a variety of facial expressions. These findings are reflected in the confusion matrix, which shows the ability of the chosen model to correctly recognize each of the expressions with an emphasis on the neutral one.

In the CK+ dataset, the model maintains a notably high accuracy, achieving a rate of 99.56%, this further reaffirms the strength of the model as there is consistency in its performance across the three datasets. Furthermore, when tested in the FER2013 database, the precision is equal to 88.5%, which means that even under realistic conditions, it successfully identifies different expressions.

The inclusion of CAM and DKA partly enhances the effectiveness and general accuracy of the model based on all defined sets. CAM improves feature capture by optimally directing focus, and DKA enhances the model's ability to generalize, making it more adaptable and effective in real-world scenarios.

Despite the high accuracy observed on the CK+ and JAFFE datasets (more than 99%), we acknowledge that such small and homogeneous datasets carry a risk of overfitting. To mitigate this, we adopted strict subject-independent evaluation protocols, ensuring no identity overlap across training, validation, or test sets. Furthermore, we conducted multiple training runs and reported mean ± std results to verify consistency. Future work will extend our evaluation to larger and more diverse datasets, such as AffectNet and Occlusion-FER, to validate generalization under real-world conditions.

6. Comparison with Different Approaches

Table 4 compares the performance of the proposed method with other state-of-the-art FER approaches that use attention mechanisms on the JAFFE, CK+ and FER2013 datasets.

The proposed MobileNetV3 + CAM + DKA model demonstrates improved performance because its three integrated enhancements include CA for spatial awareness, DKA for flexibility, and improved training stability using the SoftSwish activation function. The complete proposed model delivers better accuracy results than both the baseline MobileNetV3 and its DKA-only variant when evaluated on all datasets.

Performance gain requires accepting a more complex model structure together with additional parameters. With the addition of the CAM, the parameter count increases slightly, but the feature detection accuracy improves significantly under challenging lighting conditions and facial obstructions. With adaptive computation implemented through DKA, the model can dynamically modify kernel sizes, leading to better generalization performance without negatively affecting inference speed.

The performance strength of the LBP + CNN and Auto-FERNet methods in controlled datasets proves insufficient to address the diverse conditions of FER2013, due to limited spatial feature encoding or dependence on handcrafted features. Our method strikes a balance between performance and computational efficiency, making it more suitable for edge deployment compared to heavier models such as those based on ResNet architecture for FER tasks.

The comparison of results is presented in the Tab. 4 highlight the effectiveness of the proposed method, which integrates CA with MobileNetV3, across the JAFFE, CK+, and FER2013 datasets. Our method achieved an impressive accuracy of 98.84% in the JAFFE dataset, 99.56% in the CK+ dataset, and 88.50% on the FER2013 dataset, outperforming most other state-of-the-art methods that incorporate attention mechanisms.

Specifically, the proposed method shows a significant improvement over CNN based on the attention mechanism presented in [25], which reported precisions of 88.81%, 82.16% and 79.33% on the JAFFE, CK+, and FER2013 datasets, respectively. This substantial performance gap highlights the superiority of the coordinate attention mechanism in effectively capturing and utilizing spatial information within facial images.

Similarly, the method that involves the integration of LBP as a feature extractor and CNN network by incorporating an attention mechanism as suggested in [26] yielded slightly higher precision in the CK+ benchmark dataset at 99.48%. However, its performance drastically dropped on the FER2013 dataset with an accuracy of only 71.29%. This means that the method proposed in this work is more generalizable in different datasets while retaining a high level of accuracy, as demonstrated in the FER2013 dataset.

Furthermore, the FER method combined with the attention mechanism in [27] that produced the accuracies of 82.16%, 88.81% and 79.33% in the JAFFE, CK+ and FER2013 datasets, respectively, are relatively low compared to the huge improvements recorded by our method. The CA mechanism when combined with MobileNetV3 offers superior results in terms of spatial patterns while also outperforming other work in terms of adaptability to various datasets.

Finally, the lightweight FER with key region fusion method matches the performance of our proposed method on all three datasets. This close competition indicates that, while both methods are highly effective, the CA mechanism, when combined with MobileNetV3, provides a competitive edge, particularly in scenarios that require a balance of accuracy and computational efficiency.

7. Conclusions

In this work, we achieved a significant advancement in FER by incorporating the coordinate attention mechanism into the MobileNetV3 CNN architecture, further enhanced with dynamic kernel adaptation and SoftSwish activation. This novel combination leverages the strength of each of its constituents and, therefore, provides up-to-date, substantial improvements over the existing FER methodologies.

The approach introduced is very strong and accurate; it establishes itself as a state-of-the-art solution in the field. The proposed CA mechanism finely embeds the positional information to sharpen the model's attention on the important facial features, while MobileNetV3, with the help of DKA and SoftSwish, contributed toward high computational efficiency and adaptability to varying image complexities.

However, this study also recognized some limitations. The major limitation is that it depends on a relatively small set of experimental data and may not capture much diversity in real-world tasks. Furthermore, behavior under different lighting conditions, occlusions, and other challenging environments has not fully investigated. These drawbacks will be covered in further research by extending the evaluation with datasets that present a large diversity of lighting conditions and occlusions, as well as deepening the further contextual enhancements to make the model stronger in terms of reliability and generalization.

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