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Progressive ShallowNet for large scale dynamic and spontaneous facial behaviour analysis in children

Abdul Qayyum a,e, Imran Razzak b,* , Nour Moustafa c, Moona Mazher d

a Department of Electrical and Computer Engineering, Dijon University, France
b School of Information Technology, Deakin University, Geelong, Australia
c School of Engineering and Information Technology, University of New South Wales, Canberra, Australia
d Department of Computer Engineering and Mathematics, University Rovira i Virgili, Tarragona, Spain
e ENIB, UMR CNRS 6285, LabSTICC, Brest, France

ABSTRACT

COVID-19 has severely disrupted every aspect of society and left negative impact on our life. Resisting the temptation in engaging face-to-face social connection is not as easy as we imagine. Breaking ties within social circle makes us lonely and isolated, that in turns increase the likelihood of depression related disease and even can leads to death by increasing the chance of heart disease. Not only adults, children’s are equally impacted where the contribution of emotional competence to social competence has long term implications. Emotions are very essential for communication as well as for social interaction. Emotions play key role in decision making and are critical our daily life, i.e. how we engage with others and live our life, how we feel others emotions etc. No doubt, it is essential to remember, however, that no emotion is an island. Instead, we experience many emotions that are complex and nuanced, working simultaneously to make the varied and rich fabric of our emotional life. At times, it may seem that our emotions control us. The choices we make, the actions we take, and our perceptions are all affected by our emotions that we are experiencing at any given moment (See Fig. 1).

Emotions influence us, how we live and interact with computer. By knowing and understanding different types of human emotions, we can learn how emotions are expressed and how they can impact our behaviour. Recently, psychologists tried to understand the impact of emotions on our lives and identified several types of emotions. Several theories on emotions understanding have emerged and identify different categories and explain their behaviour that we feel. In 1970s, psychologist Paul Eckman, categorized emotions into six basic categories:

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1. Introduction

History tells us that society can be cohesive socially in crisis, and COVID-19 pandemic is presenting society with intimidating enemy that does not differentiate black and white. Resisting the temptation to engage face-to-face social connection is not as easy as we think. Breaking ties within our social circle makes us lonely and isolated, that in turns increase the likelihood of depression related disease and even it can leads to death by increasing the chance of heart disease. People strive to cope with psychological dissonance in different ways such as adjusting them-self in new ways of living. Technology also play an important role in achieving their goal.

Not only adults, children’s are equally impacted where the contribution of emotional competence to social competence has long term implications. Emotions are very essential for communication as well as for social interaction. Emotions play key role in decision making and are critical our daily life, i.e. how we engage with others and live our life, how we feel others emotions etc. No doubt, it is essential to remember, however, that no emotion is an island. Instead, we experience many emotions that are complex and nuanced, working simultaneously to make the varied and rich fabric of our emotional life. At times, it may seem that our emotions control us. The choices we make, the actions we take, and our perceptions are all affected by our emotions that we are experiencing at any given moment (See Fig. 1).

Emotions influence us, how we live and interact with computer. By knowing and understanding different types of human emotions, we can learn how emotions are expressed and how they can impact our behaviour. Recently, psychologists tried to understand the impact of emotions on our lives and identified several types of emotions. Several theories on emotions understanding have emerged and identify different categories and explain their behaviour that we feel. In 1970s, psychologist Paul Eckman, categorized emotions into six basic categories:
disgust, fear, happiness, sadness, surprise, and anger. These emotions
are experienced all over the world. Later on, Paul extended the list of
emotions to 10 emotions: embarrassment, shame, pride and excite-
ment. In the adult, even in early life such as preschool, the contribu-
tions of emotion to social competence have long-term implications on
our life.

Facial expressions are one of the efficient and effective means to con-
vey the information on one’s emotional feelings to the others. Analysis
of facial expression is very important for designing an efficient and
learnable user interface for effective communication. Deficits in the abil-
ity to understand one’s facial expressions may lead us to the impair-
ments in social functioning. Denham et al. showed that academic
achievements and peer-rated popularity are strongly correlated with
understanding the others’ emotions [5,6]. Development of emotion in
human is the largest and productive research areas in psychology. For
decades, researchers have been fascinated by it and exploring how we
respond, identify, and interpret the other’s expression. Most of the re-
search on emotional behaviour identification has relied on controlled
stimulus sets of adults emotions. However, there is less work on under-
standing children emotions. Recently, the stimulus set of emotional fa-
cial expressions (Child Affective Facial Expression, CAFE) is introduced
consisting of ethnically and racially diverse children with ages between
2 and 8-year old posing basic six basic expressions—fearful, angry, happy,
and disgusted sad, and surprised, as well as neutral face (See Fig. 2).

Children express their emotions through six expressions that are
surprise, fear, anger, disgust, anger, sadness, and happiness. Under-
standing children emotions at early stage could help to deal with poor
social functioning though efficient user interface. Most of the existing
efforts focus on facial expression recognition in adults with posed ex-
pression (artificially generation emotions). However, understanding
the behaviour in children especially the case of spontaneous facial ex-
pression is considered less comparatively. Beside, analyzing spontaneous
expressions may help to deal with deficit through development of effi-
cient user interface. To deal aforementioned challenge, in this work, we explored the problem of spontaneous emotion analysis in
children and proposed a novel end-to-end framework consisting of
lightweight ShallowNet. The key contributions of this work can be
described as

• To investigate the underlying principles of Child–Computer interac-
tion, We present novel progressive weight ShallowNet for the analysis
of spontaneous facial emotions in children.
• Unlike earlier networks, we limit the alternative path for the gradient
at the earlier stage of the network and increase gradually with the
depth of network.
• Progressive light ShallowNet is able to explore more feature space and
vulnerable to perturbations, thus it helps to overcome over fitting
challenge due to lower number of residual connections.
• Extensive experiment are conducted on benchmark facial behaviour
analysis in children for investigation of child behaviour during inter-
action with computer that showed significant improvement in detec-
tion performance comparatively.

The rest of the paper is organized as: in the next section, we present
the state of the art facial expression recognition and recent develop-
ment on spontaneous facial expression. In Section 3, we present an
alternative path based deep learning network followed by progressive
light ShallowNet and its application on child spontaneous behaviour
identification of child based on facial expression. In Section 5, we pres-
ent experimental results in detail.

2. Related work

To improve emotion recognition performance, recently, different
deep networks are individually or sequentially in different hierarchi-
cally. Dense neural networks are trained to identify the areas related
to facial expression followed by classification through autoencoder
[15]. Similarly, Liu et al. presented boasted dense neural network that
perform feature representation, feature extraction and classification it-
atively [14] which results in propagating the classification error to ini-
tiate the feature selection until it converges. To find local-translation-
invariant representation, Rifai et al. presented multi-scale contractive
neural network that identify the emotion related factors from pose
and identify hierarchically [17].

Recognition of spontaneous facial expression in children is complex
and challenging comparatively. Unlike pose expression, there are large
variations and poses, whereas spontaneous expression has lot of real
world applications such as daily interactions, meetings, and debate

| Age/Emotions | Happy | Sad | Angry | Surprised | Disgusted | Fearful |
|--------------|-------|-----|-------|-----------|-----------|---------|
| 6 Years      | 83%   | 76% | 70%   | 57%       | 30%       | 40%     |
| 7 Years      | 91%   | 85% | 78%   | 49%       | 25%       | 50%     |
| 8 Years      | 93%   | 72% | 69%   | 77%       | 39%       | 47%     |
| 9 Years      | 96%   | 76% | 76%   | 70%       | 40%       | 53%     |
| 10 Years     | 98%   | 77% | 71%   | 83%       | 42%       | 50%     |
| 11 Years     | 82%   | 73% | 72%   | 80%       | 53%       | 66%     |
| 12 Years     | 96%   | 78% | 67%   | 81%       | 62%       | 55%     |
| 13 Years     | 97%   | 78% | 73%   | 80%       | 61%       | 57%     |
| 14 Years     | 99%   | 76% | 79%   | 91%       | 75%       | 60%     |

Fig. 1. Spontaneous facial expressions.

Fig. 2. Learning of facial expressions in children.
summarization. Recently, frontal face images are localized to preserve the facial expression using generative adversarial networks [13], followed by facial expression recognition using discriminator. Similarly, GAN is used to generate images with different expression under arbitrary poses [22]. Chen et al. combined VAE and GAN to preserve the representation, which is able to disentangled the identity explicitly and generate facial synthesis while preserving the images [21].

Sequential methods such as recurrent neural networks have been applied model the semantic relationship of different face points. Chanti et al. applied grid convolution to encode the spatial correlation and used LSTM to model the temporal relationship [2]. In another work, Tran el. [19] all used 3D convolution with shared weights [1,3,4,7,23], followed by LSTM. Similarly, Vielzeuf et al used 3D convolutional kernal to compute structural score from each consecutive frame [20]. To model the time varying spontaneous expression, cascaded CNN and LSTM has also been used to model the sequential data [7,12].

Facial expression recognition has made substantial progress, however, most of the work focus on posed expression whereas real world scenarios is spontaneous expression. Beside, efforts for spontaneous expression recognition in children is comparatively less considered, whereas early detection of emotion deficits may help to prevent social functioning in later age.

3. Child–computer interaction facial behaviour analysis

Even though decades of research on understanding emotions role in user interface, there is a little understanding of how it directly manipulate our emotional compliment, undermines, or orthogonal to aspects of interface that specifically addresses the user’s need. The emotional aspects play critical role in inclusive system based on integrating the persons with disabilities. Recently, identification of human emotions have made significant progress in the past few years. However, children’s spontaneous facial expression recognition has received considerably less attention, especially that pose-invariant occlusion-robust children’s facial expressions in real-world scenarios have received significantly less attention. The deficit in early understanding of emotion as well as in skills of expression results in poor social functioning. Designing interface should consider application specific. Interface that fail to manifest or ignores user’s emotions can significantly impact the performance and risks being perceived as socially inert, untrustworthy, and incompetent. To deal with aforementioned challenges, we analyzed the spontaneous children facial expression and present lightweight progressive ShallowNet. The proposed framework is able to extract better features due to less number of residual connection locally, hence the proposed network is vulnerable to perturbations, which also solve the over-fitting issue for small data. Unlike the existing ResNet and its variants, we reduced the residual connections at earlier phase of network and graduate increased with the depth of the network. In the below section, we first discussed the proposed lightweight shallow network, followed by its applicability on the spontaneous facial expression. Fig. 3 illustrate the proposed lightweight ShallowNet.

3.1. Progressive light weight ShallowNet

Most the existing deep network for understanding emotions are over parameterized. The network that has hidden units less number of polynomially results in better classification performance comparatively than over-parameterized deeper networks. For example, each layer in DenseNet takes additional input from its preceding layers and passes it to all its following layers. Thus, each layer in DenseNet is receiving a “collective knowledge” from all its preceding layers. However, it does not only result in very complex network but also over parameterized. Similarly, Residual neural network is also over parameterize. Thus, we can say, it is natural to have numerous global optima and large training loss. In this study, we propose progressive light weight Shallow network (ShallowNet) with alternative shortcut path by leveraging the pyramidal cells in the cerebral cortex learning. Unlike, earlier networks, we decreased the number of skip connection at early stage, forcing the network to learn better representation. The proposed progressive ShallowNet architecture with additional transition block at each stage is shown in Fig. 4. Notice that the first stage in proposed ShallowNet consists of only two residual units with identify function and transition block which acts as a projection shortcut. This enables the ShallowNet to consider only features with semantic information by limiting the jump over connections. Notice, that earlier part of the network block is smaller in size, however, with the depth of network, we have increased the size of blocks that force to extract basic features with semantic information in first part of network and focus on high-level features at second part of the network. Beside this, it also speedup the learning by reducing the impact of vanishing gradient, as only few of the layers are propagated through each stage. Moreover, it allows the network to consider shallow features consisting of semantic information but not deep at each stage progressively, which helps prevent over-fitting for small data and capture feature with different level of detail. As the network grows, it gradually restores the skipped layers.

Notice (Fig. 4) that we have divided the framework into several smaller blocks. Each block further have of different number of residual unit which are different in structure (residual unit). Fig. 4 shows the proposed framework consisting of block approach. We can observe that earlier stages of network consist of smaller size residual unit with less number of skip connections. The output of each stage is forward to the transition layer, which acts as the projection matrix.

The progressive lightweight ShallowNet is based on working of pyramidal cells in the cerebral cortex. Similar to pyramidal cells, we develop small unit size in earlier blocks with less alternative path to carry additional low-level information, which helps to jump over the layers within each unit and maintain the dense connectivity. Thus, the resultant ShallowNet is less complicated, carry useful feature information and make it possible to learn hundreds of layers with much better accuracy and comparatively less training loss. Fig. 4 illustrates the proposed progressive light network architecture with alternative skip connections. Notice that we have also used the supervision layer to improve the performance, resulting in propagation of the error signal to earlier blocks efficiently and directly. This addition of implicit in-depth supervision layer in earlier small blocks with alternative paths can direct the supervision from the final block.

Traditionally, the feed-forward convolutional neural network connects the output of the mth layer as the input to $(n+1)$th layer which gives the rise to its following transition layer $x_m = H_m(x_{m-1})$. Residual neural network consist of alternative path that uses identify function to bypasses the non-linear transformations.
\[ x_n = H_n(x_{n+1}) + x_n - 1. \]

In our case, the proposed progressive light weight ShallowNet network further improves the flow between layer thorough alternative path within each block. Thus, we can write

\[ U_n = H_n([U_1, U_2, \ldots, U_i] + x_{n-1}). \]

Unlike Residual neural network, We have efficiently utilized the alternative path by dividing each units into multiple subparts and adopted the alternative path in each block and used the block’s projection path to block change, thus our proposed ShallowNet results in learning the collective features from all earlier layers. In addition to this, ShallowNet is able to go deeper than its counterpart. Each network block in ShallowNet consists of multiple skip path; however, the size of unit grows with the depth of the network, i.e. the initial block consist of 2 convolutional layers with one unit, where as next block consists of three convolutional layers with three units. Thus, the proposed network has less channels comparatively, making it thinner and deeper and extracting best feature representation (See Fig. 5).

**Table 1**

| Parameters      | Values     |
|-----------------|------------|
| Epochs          | 25         |
| Initial learn rate | $1 \times 10^{-3}$ |
| Validation frequency | 300         |
| Momentum        | 0.95       |
connections—one between each layer, however, the ShallowNet has connections in each layer whereas is the number of units and is the depth of the network on each block. In each layer of residual network, several parameters are directly proportional to whereas in ShallowNet the parameters are directly proportional to . As is the number of units and is the number of layers consist of whereas , whereas . The identity shortcuts for same dimensions is written as

\[ y = \mathcal{F}(x, \{W_i\}) + x \] (1)

### 3.2. Child–spontaneous interaction

In our early age, we learn to produce and differentiate different facial expression and play key role in decision making and are critical our daily life. Recent studies shown that children with emotion recognition are better not only studies but also in social interactions [9,10,16]. Understanding emotions are linked various outcomes and are critical for cognitive development [18]. Early deficit in emotion and expression identification may help to deal with poor social functioning. Generally, facial expression is spontaneous, thus in this work, we present an end to end recognition of spontaneous facial expression in children. We present light weight shallow-net by limiting residual connections as shown in Fig. 3.

### 3.3. Dataset

Recently, Khan et al. presented children’s spontaneous emotional database (LIRIS-CSE) consisting of children from diverse ethnicities. Video clips/dynamic images were recorded in diverse setting with six core emotions such as “happiness”, “sadness”, “disgust”, “anger”, “surprise”, and “fear”. The expression are same as of other facial expression datasets for adults. The unconstrained videos are recorded with the constraint-free environment such as children were free to move their head and hand in the free sitting environment. There were no restriction on kids were applied during dataset collection while they were watching special build images. The dataset was labelled and rated by 22 human rates. LIRIS-CSE consists of 26,000 frames of kids emotions. As kids were recorded in constraints free environment, thus, their expression is natural and spontaneous.

### 4. Experiment

User Interface design should mainly focus on application specific goals. Even though years of research, there is a little understanding that how a user interact is directly impacted by our emotion. Recently, identification of human emotions have made significant progress in the past few years. However, children’s spontaneous facial expression recognition has received considerably less attention, especially that pose-invariant occlusion-robust children’s facial expressions in real-world scenarios have received significantly less attention. Children’s spontaneous facial expression recognition has received considerably less attention, especially that pose-invariant occlusion-robust children’s facial expressions in real-world scenarios have received significantly less attention. The deficit in early understanding of emotion and expression skills results in poor social functioning. In this section, we present experimental setup, results and evaluation of proposed framework on benchmark child spontaneous facial expression dataset. Tables 4 and 5

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**Table 2**

|                       | Support | Recall | Precision | Recall | F1-score |
|-----------------------|---------|--------|-----------|--------|----------|
| Disgust               | 97      | 1.00   | 1.00      | 1.00   | 1.00     |
| Fear                  | 529     | 0.98   | 0.99      | 0.98   | 0.99     |
| Happy                 | 778     | 0.99   | 1.00      | 0.99   | 0.99     |
| Sad                   | 512     | 1.00   | 0.99      | 1.00   | 0.99     |
| Surprise              | 546     | 0.99   | 0.98      | 0.99   | 0.98     |

| Macro avg.            | 2462    | 0.99   | 0.99      | 0.99   | 0.99     |
| Weighted avg.         | 246     | 0.993  | 0.994     | 0.993  | 0.992    |

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**Table 3**

| Model                        | Precision | Recall | F1-score |
|------------------------------|-----------|--------|----------|
| Proposed Shallownet network  | 0.994     | 0.993  | 0.992    |
| DenseNet-freeze              | 0.94      | 0.95   | 0.94     |
| ResNet-freeze                | 0.97      | 0.97   | 0.97     |
| Inception-freeze             | 0.97      | 0.97   | 0.97     |
| MobileNet-freeze             | 0.95      | 0.95   | 0.95     |
| DenseNet-fine-tuned          | 0.88      | 0.88   | 0.88     |
| ResNet-fine-tuned            | 0.90      | 0.89   | 0.89     |
| Inception-fine-tuned         | 0.90      | 0.90   | 0.90     |
| MobileNet-fine-tuned         | 0.88      | 0.87   | 0.87     |
| Khan et al. [11]             | 0.81      | 0.82   | 0.83     |

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**Figure 6.** Confusion matrix.

**Figure 7.** Comparison of ROC curve of proposed progressive light residual learning with state of the art transfer learning methods using freeze scenario.
and Figs. 7 and 8 illustrate the experimental results. To generalize the performance gain, we have performed 10-fold cross-validation and compared the performance using different evaluation measures such as precision, recall, F-score, specificity, sensitivity, specificity and area under the curve (AUC).

4.1. Network parameter

Progressive lightweight ShallowNet architecture consists of smaller initial units with additional supervision block and transition blocks. Initial blocks consist of 2 convolution layer of $3 \times 3$ followed by batch normalization. Block 1 is followed by an alternative project path. Block 2 consists of 2 subunit, consisting of convolution layers ($3 \times 3$ and batch normalization followed by transition and supervision blocks). To learn the best possible feature representation, ShallowNet has fewer alternative paths with smaller unit size in earlier blocks. We have increased the number of alternative path and unit size in later stages. We have initialized the weights as in [8] and trained the network from scratch. In order to find the best parameters and see the impact of the parameter in each block, we have trained ShallowNet network on different parameter values for each block. We have set the learning rate to $(1 \times 10^{-3})$ and momentum of $(0.95)$. We have stopped the training when there is no change in error rate for 25 epochs. Notice that the size of the kernel is continuously increasing with the growth of the network. Table 1 describes the training parameters.

4.2. Results

To visualize the robustness of network, we performed different experiments with different parameters and variations in network structure i.e. 2 Blocks, 3 Blocks with variable residual units. In order to generalize the performance, we have performed k-fold cross-validation ($k = 10$) and compared the performance with start-of-the-art methods. We have evaluated the performance using different evaluation metrics such as the precision, recall, F-score, sensitivity, specificity and area under the curve (AUC). Table 4 describes the emotion recognition results for each class. Notice that, we have achieved high accuracy for disgust emotions followed by 'happy'. Similarly, we can notice the trend for other emotions. Fig. 6 shows the confusion matrix of the proposed progressive light residual network. It shows that proposed ShallowNet achieved significantly better performance comparatively, however, it is worthy to highlight that performance is slightly poor for 'fear' (See Tables 2 and 3).

Tables 4 and 5 showed that progressive lightweight ShallowNet network achieve best performance 0.99 (F1 score), 0.99 (recall) and 0.99 (precision) on 2462 images. Notice that disgust and happy expressions showed better performance with almost no false rate (see confusion matrix in Fig. 6). In addition to this, we have also applied transfer learning using several state-of-the-art methods, especially counter networks such as Inception, MobileNet, ResNet, and DenseNet. We have considered both freeze and fine turning in transfer learning. We applied the transferability of deep models trained for facial expression recognition on adults expression dataset (source) to the children expression (target). Tables 5 and 4 shows that proposed progressive lightweight ShallowNet showed significant improvement results compared to the baseline methods as as as state of the art transfer learning methods.

4.3. Discussion

Unlike, earlier work on adult or child facial recognition based on posed expression (fake or disguise inner feeling), we focused on solving the problem of expression in spontaneous expressions captured in an unconstrained environment. In this section, we have compared the performance with state of the art methods (See Figs. 9 and 10).

| Average Accu | Average precision | Average recall | Average F1-score |
|--------------|------------------|----------------|------------------|
| Proposed     | 99.06            | 99.16          | 99.22            | 99.19            |
| SqueezNet    | 86.92            | 89.25          | 82.20            | 84.46            |
| DensNet121   | 87.65            | 86.95          | 86.94            | 86.78            |
| ResNet101    | 90.37            | 89.98          | 84.28            | 86.41            |
| Inception_V3 | 89.27            | 90.26          | 88.83            | 89.45            |
| MobileNet_v2 | 87.32            | 85.60          | 88.68            | 86.71            |
| Deep-CNN [11]| 77.23            | 69.43          | 77.88            | 81.44            |

Fig. 8. Comparison of Precision–Recall curve of proposed progressive light residual learning with state of the art transfer learning methods using freeze scenario.

Fig. 9. Analysis of performance of proposed progressive light weight ShallowNet.

Fig. 10. Comparison of predicted vs test values.

Table 4

Comparative analysis (average) of ShallowNet framework with its counter network (Inception, MobileNet, DenseNet, ResNet and SqueezNet).
In addition to this, we have applied transfer learning using several benchmark methods, especially counter networks such as ResNet, MobileNet, Inception and DenseNet. We have considered both freeze and fine turning in transfer learning. Tables 4 and 5 shows that proposed progressive lightweight ShallowNet showed significant improvement results compared to the baseline methods as as state of the art transfer learning methods. We can notice that our proposed network showed the significantly better performance to 99.18% in comparison to 97.01% and 96.81% for Inception and ResNet, respectively, as our approach is a variant of ResNet. The significant gain in classification performance compared to ResNet showed the robustness of the proposed network for complex and relativity small dataset problems. From Tables 5, and Figs. 7, 11, and 8 we can notice that fine-tuning showed considerably better performance in comparison to freeze network. Furthermore, we can also notice that our proposed approach achieved significantly better performance than state-of-the-art methods (See Fig. 12).

Comparing with benchmark emotion classification methods, we have the following interesting observations.

- Progressive light weight ShallowNet converges faster compared to counter network.
- Progressive lightweight ShallowNet can extract better representation due to fewer skip connection at the earlier part of the network.
- Progressive ShallowNet showed better performance with the increase of network depth for the larger dataset.
- Progressive light ShallowNet has much lesser parameters comparatively.
- The proposed ShallowNet showed a significant gain in performance and reduced the top error successfully. This shows the effectiveness of proposed progressive light network over its counter network, which validates its robustness, hence it can be applied to many other classification problems efficiently.

Table 5
Comparative analysis (average) of proposed framework with its counter network (ResNet, MobileNet, DenseNet and SqueezNet using Freeze based fine tuning).

|       | Accuracy | Precision | Recall  | F1-score |
|-------|----------|-----------|---------|----------|
| Proposed | 99.06    | 99.16     | 99.22   | 99.19    |
| SqueezeNet | 86.92    | 89.25     | 82.20   | 84.46    |
| DenseNet121 | 87.65    | 86.95     | 86.94   | 86.78    |
| ResNet101 | 90.37    | 89.98     | 84.28   | 86.41    |
| Inception_V3 | 89.27    | 90.26     | 88.83   | 89.45    |
| MobileNet-v2 | 87.32    | 85.40     | 86.88   | 86.71    |
| Deep-CNN [11] | 77.23    | 69.43     | 77.88   | 81.44    |

Fig. 11. ROC curve comparative analysis with transfer learning based on fine-tuned network.

5. Conclusion

In this paper, we addressed the role of children's emotions in human computer interaction. Emotions are an important part of the human–computer interaction especially in children. Multimodal interfaces that include facial expression and voices can manifest large range of nuanced emotions than was possible in purely textual interfaces. Interface that fails to manifest or ignores user's emotions can significantly impact the performance. We presented light weight progressive ShallowNet learning to classify spontaneous emotion recognition in children. Unlike earlier residual network, we limit the residual connection in the earlier phase of network and increased gradually with the growth of network which can learn robust features due to less number of residual connection. Hence, the proposed network is vulnerable to perturbations which helps to overcome overfitting issue for smaller data. Extensive experimental on benchmark children facial expression dataset showed that proposed framework is significantly better with performance to 99.16% in comparison to 90.37%, 86.82, and 87.65% using ResNet, DenseNet and SqueezNet, respectively. The significant gain in performance compared to its counter network showed the robustness of proposed ShallowNet for complex and relativity small dataset problems.

Credit author statement

Abdul Qayyum, Mona Mazhar and Imran Razzak performed experiment. Mona Mazhar and Nour Mustafa analyzed the results and Imran Razzak and Nour Moustafa wrote the manuscript.

Declaration of Competing Interest

Authors declare no conflict of interest.

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