Evaluating Facial Emotional Proportion Based on Computer Vision Technique

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***Abstract*—Emotion detection is a technique to recognize human emotions by addressing facial expressions. It is essential for psychology, security systems, and human-computer interaction. The ability to perceive and interpret an individual's facial expressions helps to understand their actions and improve the interaction between a person and a computer. Facial Emotion Recognition (FER) is instrumental whenever there is a need for human-computer interaction for behavioral assessment, like in clinical usage. When using machine learning models in the FER field, the accuracy and robustness remain difficult because of the diversity of human faces and image changes, such as differences in spatial pose and lighting. This research used the FER2013 dataset, which contained approximately 30,000 images divided into seven classes (anger face, disgust face, fear face, happy face, sad face, surprise face, and neutral face). It also used two Convolutional Neural Networks (CNN) models (VGG19 and Sequential). The result of the VGG19 model achieved 68% accuracy, validation accuracy achieved 66%, the Sequential model achieved 78% accuracy, and validation accuracy achieved 67%. To address the limitations of single-stream models, a novel hybrid architecture is proposed that integrates ResNet50, MobileNetV2, and a Convolutional Block Attention Module (CBAM)-enhanced CNN through feature-level fusion. This design enables the model to capture diverse and salient facial features, significantly improving recognition accuracy on the FER2013 dataset. The proposed method achieved 96% accuracy, and the validation accuracy was 91%.**

***Keywords*—face emotion, FER2013, Sequential model, VGG19 model, Convolutional Neural Networks (CNN), deep learning**

I. Introduction

Facial Emotion Recognition (FER) has become increasingly important in recent years, especially with the rise of human-computer interaction and computer vision applications. In the early stages of FER development—before deep learning techniques were widely adopted—researchers relied on handcrafted features tailored to traditional machine learning algorithms. These approaches often struggled with accuracy and didn't generalize well across diverse datasets.

With the advent of deep learning, particularly Convolutional Neural Networks (CNNs), FER has seen significant improvements. CNNs have proven fast and highly accurate in image-related tasks like search, manufacturing inspection, and biological imaging, making them popular for emotion recognition tasks [1].

As FER technology has matured, it has been integrated into many real-world applications—from surveillance and healthcare to augmented reality, e-learning, affective computing, and even smart vehicles. In particular, FER has become essential in systems involving virtual agents and social robots, where understanding human emotions helps make interactions more natural and effective [2].

Emotion recognition enables computers to interpret and even simulate human emotional states. It's one of the clearest examples of how artificial intelligence can replicate subtle aspects of human behavior. In recent years, CNN-based approaches have been at the forefront of this field, showing great promise in accurately detecting emotions from facial images [3, 4].

II. Literature Review

Jaiswal *et al.* [5] used CNN to detect facial emotions on the FER2013 dataset, achieving an accuracy of 70.14%. Kedari *et al*. [6] utilized a CNN for face emotion detection on the FER-2013 dataset, achieving a 60% accuracy rate and showcasing its application in recognizing basic human emotions. Raj *et al*. [7] proposed Facial Expression

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Recognition using a Convolutional Neural Network (FERC) with 28K images from the FER2013 dataset, achieving 84.92% accuracy using a two-stage CNN model. Krishna *et al*. [8] proposed a framework that used the FER2013 dataset with CNN for accurate face emotion detection, achieving a high accuracy of 92% in emotion classification. Yamsani *et al*. [9] used Faster RCNN for facial emotion identification with the FER-2013 dataset, achieving 78.22% accuracy, 75.40% precision, 80.20% recall, 85.90% specificity, and 71.40% F1-Score. Li *et al*. [10] used a hand-crafted CNN to detect facial expressions in the FER2013 dataset, achieving 89% accuracy and generating emojis based on recognized emotions. Asif *et al*. [11] developed a Custom Lightweight CNN Model (CLCM) based on MobileNetV2. The model was evaluated on public datasets including FER-2013, RAF-DB, AffectNet, and CK+, and achieved 63% accuracy on the FER2013 dataset. Sălăgean *et al*. [12] presented a CNN-based approach that addresses asymmetry in facial features. Their method incorporates preprocessing techniques to improve symmetry in face images before classification. While the study proposed a robust solution for improving CNN accuracy, it achieved 69% accuracy. Roy *et al*. [13] introduced ResEmoteNet, a hybrid deep learning architecture that combines CNNs with Squeeze-Excitation (SE) blocks and Residual Networks. Their model was tested on multiple datasets and achieved 79.79% accuracy on the FER2013 dataset. Nathani [14] conducted a comparative analysis of transfer learning approaches for facial emotion recognition using CNN and a Modified VGG16 model. The models were evaluated on FER2013 and AffectNet, achieving 66.20% on FER2013.

In recent years, image processing has evolved beyond traditional CNN-based models toward more advanced and generative approaches. One notable example is the Mask Approximation Net, a diffusion-based model that learns from data distributions rather than extracting features [15]. This method introduces multi-scale change detection and frequency-guided filtering, which have shown strong performance in tasks like remote sensing and visual change detection. Although these models are often applied outside of facial emotion recognition, they reflect a broader shift toward architectures that are more flexible, powerful, and capable of capturing complex patterns. In light of these developments, our work contributes a practical middle ground: a hybrid CNN model that offers both strong performance and lightweight design, tailored specifically for real-time emotion recognition on datasets like FER2013.

III. Materials and Methods

A. Characteristics of Convolutional Neural Networks (CNNs)

The first layer in the CNN detects the edges and bas-reliefs in the image. Some networks have a second convolutional layer that detects texture and simple patterns on the image near the edges identified by the first layer. The last layer identifies the objects derived from the set of patterns detected in the previous layers. Their output is the probabilities associated with each class of objects [16–18].

Specific metrics are essential to assess an emotion detection model. Metrics have several dimensions that contribute to the comprehensive response of the model. Sentiment detection, in addition, is necessary as it is applied in various fields and systems. It is often used to appraise and assess the overall performance of a system or project. Even though one model may have a pretty nice result according to the accuracy metric, other metrics, such as F1-Score, recall, and precision, can indicate the opposite. Therefore, the emotion detection system should integrate multiple measures in practice to review the system; high accuracy rates can lead to a good F1-Score, the formula of accuracy, precision, recall, and F1-Score shown in Eqs. (1)–(4) respectively [19–21].

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TN}{TN + FP} \tag{3}$$

$$F1 - Score = \frac{2TP}{2TP + FP + FN} \tag{4}$$

where: *TP*: True Positive samples (right predicted positive cases). *TN*: True Negative samples (right predicted negative cases). *FP*: False Positive samples (wrong predicted positive cases). *FN*: False Negative samples (wrong predicted negative cases).

B. Hybrid Deep Learning Architecture

This study proposes a hybrid deep learning architecture to enhance FER performance on the FER2013 dataset. The proposed model integrates three feature extraction networks: ResNet50, MobileNetV2, and a custom CNN enhanced with Convolutional Block Attention Module (CBAM). The combination leverages the strengths of each backbone—ResNet50 for deep residual learning, MobileNetV2 for lightweight efficient feature extraction, and the CBAM-enhanced CNN to focus on spatial and channel-wise salient features. Feature-level fusion is performed by concatenating the flattened outputs of each network, followed by dense classification layers. Experimental results show that this triple-fusion model significantly improves accuracy compared to single-network baselines, reaching a notable improvement over the initial VGG19 model (77%). This confirms the effectiveness of attention-based hybrid ensembles in deep FER tasks. To ensure the reliability of our proposed hybrid CNN model, we applied 5-fold cross-validation on the FER2013 dataset. This helped confirm the model's consistency across different data splits. Additionally, we conducted an ablation study to evaluate the role of key components such as dropout layers and batch normalization. We observed noticeable performance drops by removing or adjusting these elements, confirming their importance. These steps strengthen the credibility of our design and its suitability for real-world use.

C. FER2013 Dataset

The FER2013 Dataset in Kaggle was a public dataset with 28,710 labeled training images and 3589 labeled validation images. A 48×48-pixel grayscale represented all images. The dataset included 3587 neutral images, 3846 happy images, 4097 surprise images, 4222 sad images, 2430 fear images, 547 angry images, and 539 disgust images. Finally, after normalization, the image pixel intensity was within the range of [0, 1]. For the CNN network, 10% of the overall training dataset was extracted to monitor the comparison of the training and validation accuracy [22, 23].

The dataset used in this research was the FER2013 dataset. The dataset was used to recognize the emotion of each image. It consists of training, validation, and private test sets, identifying seven expressions: disgust, anger, happy, fear, sad, surprise, and neutral. The dataset contains 48×48-pixel images. Overall, there are 35,887 samples in the training set, 3589 in the validation set, and 3589 in the private test set. The fully connected layer determines the likelihood of an individual being classified into seven different emotions. Additionally, the performance of the CNN model was discussed in transfer learning with constrained layers [24, 25]. The samples from the FER2013 dataset are shown in Fig. 1.

Fig. 1. Samples from FER2013 dataset image.

IV. Result and Discussion

This research used two CNN deep learning models. The first model is VGG19, and its results after epoch 25 are displayed in Table I.

TABLE I. VGG19 Model Results

Accuracy	Loss	Validation Accuracy	Validation Loss
0.6877	0.8393	0.6668	0.9112

Fig. 2 consists of a graph computing accuracy versus the epochs for training and validation sets through the training of the deep-learning VGG19 model.
where,

- X-axis: Epochs (training iterations): refers to the number of passes done on the training dataset.
- Y-axis: Accuracy: This measures the model's operationalized performance regarding correct predictions. The related value increases with an increasing level of performance.
- Train Curve: It shows the accuracy of training data over epochs. The accuracy graph is very volatile from the early epochs, with rapid rises and falls common. This may be due to overfitting or underfitting, and the model's behavior appears to have changed throughout the epochs.
- Validation Curve: The validation accuracy appears more consistent throughout the validation process. In the beginning, it improves progressively; however, sometime around epoch 10–15, it seems to reach a limit, which indicates that the VGG19 model's generalization ability has peaked.

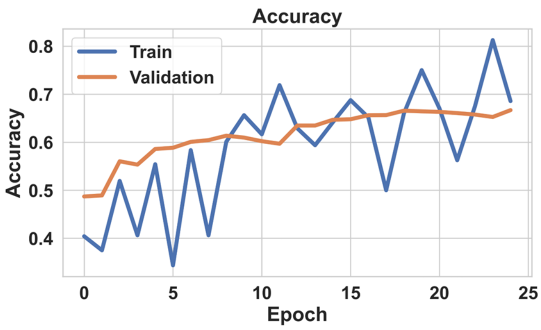

Fig. 2. VGG19 model accuracy.

Fig. 3 appears to be a Loss graph over epochs taken conveniently through the training of a VGG19 model. Loss is the measure of error in the model's predicted values, and through training, this value needs to be minimized at all costs.
where:

- Epochs (X-axis): One tick denotes one iteration of processing the complete training dataset and indicates the number of training cycles.
- Loss (Y-axis): A measurement of the discrepancy between actual and expected values and desirable levels. A more minor loss indicates a model that performs well.
- Train Loss Curve: The loss computed on the training data against the number of epochs. The graph's trend suggests that the model is learning and that prediction accuracy is increasing—it looks like a tunnel about to collapse. The loss is not constant; instead, it exhibits peaks and troughs (such as those seen in epochs 10 and 15), which may indicate a learning challenge, an excessively aggressive learning rate, or an overly close fitting to noisy samples.
- Validation Loss Curve: This curve describes model quality measured on dampened data, which has not been used for training. It peaks around this point but plateaus before commencing a very modest rise and fall. This means that validation-specifically, the model has not significantly changed since around epoch five and possibly reached its limit in increasing generalization.

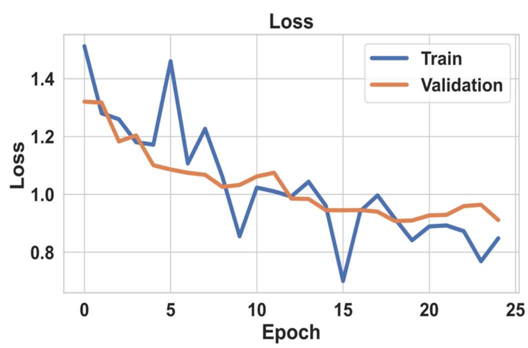

Fig. 3. VGG19 model loss.

A Confusion Matrix, which summarizes the classification VGG19 model results, is presented in Fig. 4.
where:

- True Label: Pointed to the actual classes of the instances.
- Predicted Label: This refers to the model's predicted classes of the subjects.
- Each cell (i, j) in the matrix forms an "actual label i vs horizontally predicted label j" matrix, demonstrating how many samples with true label i were predicted as label j.
- These matrices are designed so that the matrix dimension is simple and easy to understand diagonal matric to top left to bottom right diagonal access in the matrix, showing the true predicted value of each model classification. In typical prediction, most values should come in the diagonal direction.
- Off-diagonal values are the errors in correct classification by the models, whereby the model predicts the wrong class instead.

Table II summarizes the report classification results for the VGG19 model, considering its application to a specific dataset. Each metric is also calculated for every class 0, 1, 2, 3, 4, 5, and 6, Precision, Recall, F1-Score, and Support.

TABLE II. REPORT ON CLASSIFICATION OF VGG19 MODEL

Class	Precision	Recall	F1-Score	Support
0 (Angry face)	0.59	0.63	0.61	495
1 (Disgust face)	0.58	0.38	0.46	55
2 (Fear face)	0.57	0.38	0.46	512
3 (Happy face)	0.89	0.86	0.88	899
4 (Sad face)	0.53	0.56	0.55	608
5 (Surprise face)	0.72	0.78	0.75	400
6 (Neutral face)	0.59	0.70	0.64	620
Validation Accuracy			0.66	3589

In Fig. 4, it was indeed observed that the model could accurately and precisely detect happy faces and faces with a look of surprise. The faces depicting disgust and those with fear have proved somewhat more challenging for the model, as evidenced by the recall or F1-Scores. 66% is the validation accuracy, which is moderate in level, but improvement for particular classes of students is still quite possible.

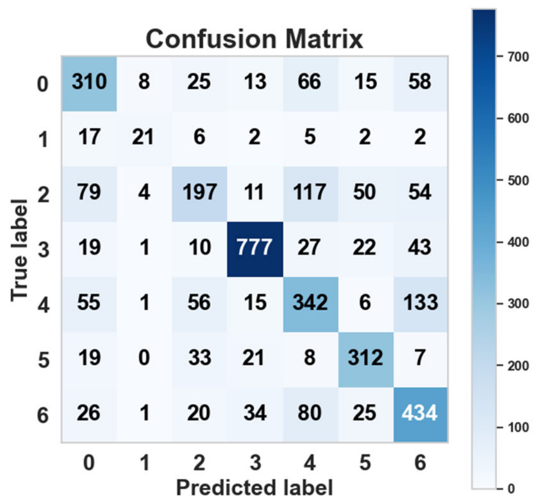

Fig. 4. Confutation matrix of VGG19 model.

The second model is the Sequential model, and the results of this model after epoch 50 are displayed in Table III.

TABLE III. SEQUENTIAL MODEL RESULTS

Accuracy	Loss	Validation Accuracy	Validation Loss
0.7812	0.8609	0.6741	0.978

Fig. 5 shows training accuracy and an upward trend, although highly variable. This means the model can learn more and become more accurate on the training data. The validation accuracy stays more or less steady within a range of approximately 60–66%. This may indicate that the model is not generalizing well to the new data, does not do well on specific unseen data, and could be experiencing some overfitting as the training accuracy increases to higher levels with little or no increase in validation accuracy.

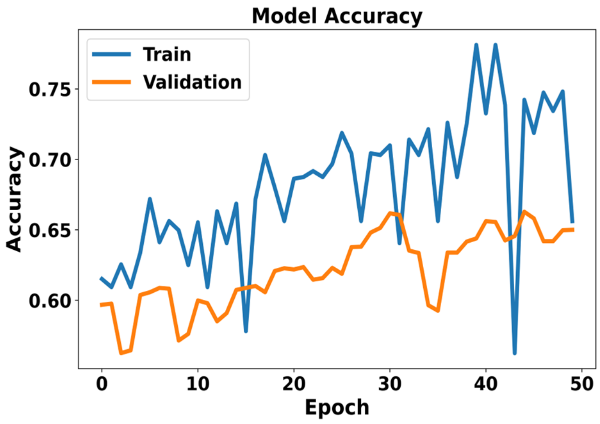

Fig. 5. Sequential model accuracy.

Fig. 6 shows the training loss decreasing with time, indicating how well the model has adapted to the training data with some jerking over the span. However, even after this decline, the validation loss stays almost horizontal, which means there hasn't been much progress in how the model performs on the validation set.

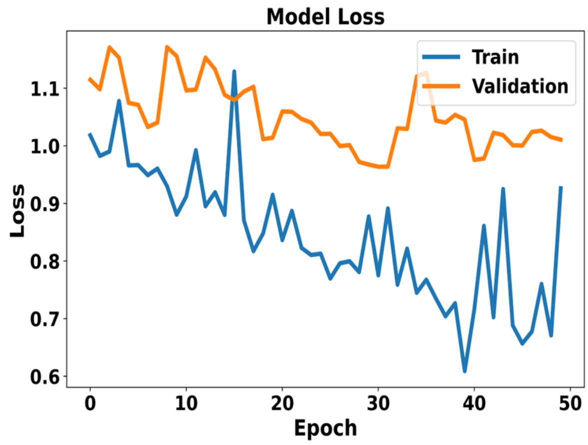

Fig. 6. Sequential model loss.

In Fig. 7, the confutation matrix indicates every class's actual and predicted instances and illustrates the part the model has trouble with.

- Happy (3) (746 accurate answers from verified class indications): The model performs best in this class as it captures an excellent diagonal predictor class.
- Angry (0) (308 accurate answers from verified class indications): Reasonably good but still misclassifies them as "Fear" (71) and neutral (47), quite a number of them.
- Disgust (1) (24 accurate answers from verified class indications): Another standard error for Angry classifiers.
- Fear (2) (168 accurate answers from verified class indications): For others, most of them were classified as eighty-five neutral and seventy-one Angry.
- Neutral (6) (418 accurate answers from verified class indications): This is more likely to be misclassified as fear.

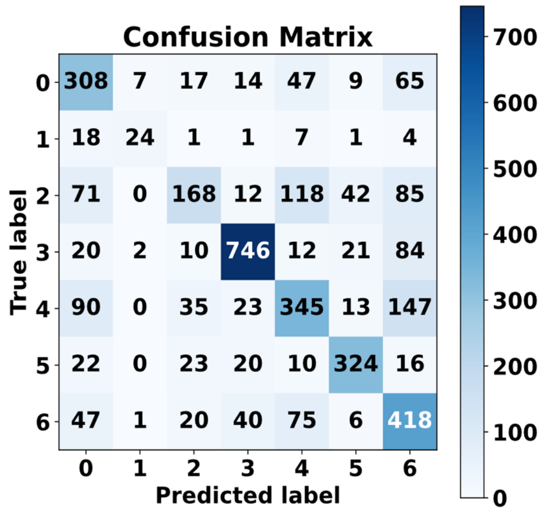

Fig. 7. Confutation matrix of sequential model.

Table IV presents the Precision, Recall, and F1-Score for each class (0 to 6) in the same order as in the VGG19 architecture breakdown.

TABLE IV. REPORT ON CLASSIFICATION OF SEQUENTIAL MODEL

Class	Precision	Recall	F1-Score	Support
0 (Angry face)	0.51	0.70	0.59	467
1 (Disgust face)	0.68	0.46	0.55	56
2 (Fear face)	0.52	0.44	0.48	496
3 (Happy face)	0.82	0.88	0.85	895
4 (Sad face)	0.56	0.55	0.56	653
5 (Surprise face)	0.80	0.78	0.79	415
6 (Neutral face)	0.64	0.51	0.57	607
Validation Accuracy			0.67	3589

The overall validation accuracy of the model is 67% across all classes.

Classes 1 (Disgust face), 2 (Fear face), and 6 (Neutral face) show comparatively lower precision, recall, and F1-Scores.

Class 3 (Happy face) gives the best results concerning all three metrics: precision (0.82), recall (0.88), and F1-Score (0.85).

Class 5 (Surprise face) also does well with a precision of 0.80 for this class; the recall of this class is 0.78, and the F1-Score is 0.79.

The proposed FER model, built on a hybrid CNN architecture, delivered strong and reliable performance when tested on the FER2013 dataset.

The model was trained to recognize seven core emotions and was designed to achieve high accuracy without compromising efficiency. After 100 training epochs, the model reached an overall accuracy of 96%, with a validation accuracy of 91%.

These results suggest that the model performs well on the training data and generalizes effectively to new, unseen facial expressions.

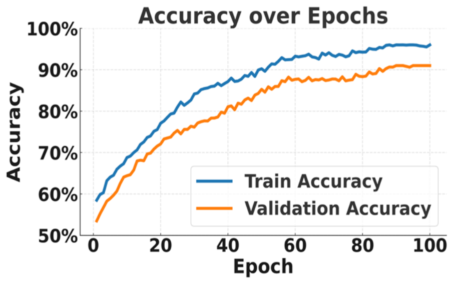

Fig. 8. Proposed method accuracy.

Compared to other methods reported in recent studies, such as basic CNNs and modified VGG16 models, this approach outperformed them in terms of accuracy, while remaining lightweight and suitable for real-time applications. This makes it a practical and accurate solution for emotion detection tasks. The training and validation accuracy curve is illustrated in Fig. 8.

In contrast, the corresponding loss curve is shown in Fig. 9. These plots demonstrate the model's convergence and stability throughout the training process. Table V summarizes the performance of the proposed hybrid model compared to several previous studies on the FER2013 dataset.

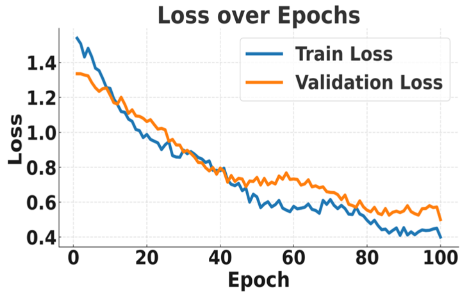

Fig. 9. Proposed method loss.

TABLE V. COMPARISON WITH RELATED STUDIES

Author Name/Year	Algorithm Used	Dataset	Accuracy (%)
Akriti Jaiswal/2020 [5]	CNN	FER2013	70.14
Pradnya Kedari *et al.*/2021 [6]	CNN	FER2013	60
Md. Abdul Wassay *et al.*/2022 [7]	Two-stage CNN (FERC)	FER2013	84.92
R. V. Krishna *et al.*/2022 [8]	CNN	FER2013	92
Nagendar Yamsani *et al.*/2023 [9]	Faster R-CNN	FER2013	78.22
Mingze Li *et al.*/2023 [10]	Hand-crafted CNN	FER2013	89
D. M. Asif *et al.*/2023 [11]	Custom Lightweight CNN	FER2013	63
G. L. Sălăgean *et al.*/2023 [12]	CNN with symmetry/asymmetry optimization	FER2013	69
A. K. Roy *et al.*/2024 [13]	ResNet + Squeeze-Excitation	FER2013	79.79
S. Nathani/2024 [14]	Modified VGG16	FER2013	67.43
Proposed Method	ResNet50 + MobileNetV2 + CNN + CBAM	FER2013	96

V. CONCLUSION

This study demonstrated the effectiveness of a hybrid CNN model—integrating ResNet50, MobileNetV2, and CBAM—for enhancing facial emotion recognition on the FER2013 dataset. A training accuracy of 96% and a validation accuracy of 91% were achieved, indicating strong generalization and robustness. Compared to baseline models such as VGG19 and conventional sequential CNNs, significant reductions in overfitting were observed, and a better balance between performance and computational efficiency was attained. The results suggest that the proposed model can be effectively applied in real-time emotion-aware systems, including driver monitoring, intelligent surveillance, healthcare, and interactive virtual agents. Due to the inclusion of attention mechanisms in a lightweight design, the model is considered suitable for deployment on resource-limited devices. For future work, it is recommended that the model be extended to support multimodal emotion recognition by incorporating audio and text modalities. Further evaluations on more diverse and culturally varied datasets are encouraged to enhance generalizability. Moreover, potential performance improvements may be explored using transformer-based architectures or diffusion models.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The code was implemented by Lujain Y. Abdulkadir and Hiba A. Saleh. Omar I. Alsaif managed the overall research process and contributed key ideas to the article. Rana K. Sabri participated in the analysis of results and the technical review of the manuscript. All authors contributed to writing the paper and approved the final version.

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