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RESEARCH ARTICLE

CNN-MPFM: Deep Learning Based Face Recognition for Healthcare Patient Monitoring Systems

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Abstract Face recognition is one of the techniques used to identify and classify individuals that has distinctive features of their face for automated healthcare monitoring. Intelligent face analysis is indispensable in the medical field for improving patient safety, rapidly assessing patient status, and live monitoring. However, many existing methods rely on conventional facial analysis or basic classifiers, which limits recognition accuracy and reduces performance under varying facial expressions and real-time conditions. To overcome these restrictions, a Convolutional Neural Network with MediaPipe Face Mesh (CNN-MPFM) model is proposed. Initially, the input patient facial images are preprocessed using face detection, resizing, and normalization. The output of the processed facial images is then passed to the MediaPipe Face Mesh module, which provides more detailed facial information with precise facial landmark coordinates and structural facial information. CNN model is an intelligent classification to determine if patient is in normal or suffocated condition, given the prominent features that were retrieved. The suggested CNN-MPFM framework is evaluated with accuracy, precision, recall, F1-score, loss and classification efficiency. The experimental analysis results show that the accuracy, precision, recall, and F1-score of the suggested CNN-MPFM method are 99.52%, 99.46%, 99.49%, and 99.47% respectively. Furthermore, the proposed CNN-MPFM approach enhances the classification accuracy over the previous deep transfer learning, ConvNet, MobileNet-V1 and multi-modal recognition approaches.

Keywords *– Deep Learning, Face Recognition, Healthcare Systems, Patient Monitoring and Convolutional Neural Network.*

1. INTRODUCTION

Face recognition in healthcare patient management systems has become essential due to the rapid growth of digital healthcare services, smart hospitals, and automated monitoring environments [1]. For successful clinical operations, these systems must be able to identify patients reliably, in a contactless manner and be constantly monitored [2]. Conventional manual identification techniques are laborious and prone to mistakes, and inefficient in handling large patient volumes [3]. Face Recognition is an effective biometric technique, which is based on the distinctiveness of facial features for identification and validation of individuals. [4]. However, traditional face recognition methods are not very effective when the lighting condition changes, posture changes, facial expressions, or partial occlusion [5]. Thus, the challenge of obtaining accurate and efficient face recognition is still a difficult one in the patient management systems in health care.

A few models based on ML and DL have been proposed to solve these problems [6]. The moderate recognition performance of conventional methods like PCA, LBP and SVM methods do not represent the complex facial representation [7]. Transfer learning-based frameworks have been shown to enhance the recognition accuracy but they tend to demand vast amounts of training data and more computational resources [8]. Facial landmark-based systems augment the analysis of facial structure but may not be as efficient when under real time monitoring conditions [9]. Likewise, CNN based face recognition models are found to have better classification capability, whereas certain models suffer from the problem of overfitting and have lesser generalization on unseen patient images [10]. Other existing work also involves complex pre-processing pipelines that result in a higher computational delay and less real time applicability [11,12].

To overcome these problems, CNN-MPFM model is proposed to address the challenges of intelligent patient monitoring in healthcare and face analysis in media pipe face mesh [13,14]. The proposed CNN-MPFM processes the input facial image by performing the processing in pre-processing phase, namely face detection, resizing and normalization, to facilitate efficient analysis [15]. Then, MediaPipe Face Mesh is used to compute accurate 2D facial landmark coordinates and facial structural features online, which reduces the computation complexity [16]. The extracted landmark features are transmitted to CNN model for effective patient condition classification based on discriminative facial patterns learned [17]. For healthcare monitoring application, the output images are classified as normal (or suffocated) images [18]. Last but not least, the classified results can be fed to smart hospital systems for timely decision making, patient safety, and automated monitoring support [19,20]. Proposed CNN-MPFM model is more accurate in classification than existing, less time consuming in processing and more efficient in healthcare monitoring. Major contributions of CNN-MPFM method are given below.

- ♣ Primary objective of proposed CNN-MPFM method is to build an intelligent and efficient healthcare monitoring system to enhance patient condition classification by analyzing the facial image.
- ♣ The proposed CNN-MPFM approach involves using MediaPipe Face Mesh to obtain the precise facial landmark points for the accurate real-time representation of the facial features.
- ♣ The model used is a CNN that is capable of effectively identifying the discriminative facial patterns and categorizing the patient conditions into normal and suffocated classes.
- ♣ TThe proposed framework uses preprocessing method of the image like face discovery, resizing, normalization of image to get the better quality of the image and to improve the performance of classification.

The experimental results demonstrate that proposed CNN-MPFM method has a higher classification accuracy, precision, recall, and F1-score with applications in healthcare monitoring. Proposed framework is realised in Python.

Remainder paper is organized as follows: The literature survey about healthcare face recognition and patient monitoring systems are described in section 2. The suggested CNN-MPFM methodology for patient condition classification is explained in Section 3. Routine of suggested model is examined in Section 4 using several assessment measures. Finally concluded and upcoming work is discussed in Section 5.

2. LITERATURE SURVEY

Recent advancements in DL technologies have significantly upgraded face recognition and healthcare monitoring systems by enhancing feature extraction, classification accuracy, and intelligent decision-making performance. In recent years, various models have been proposed to support facial diagnosis, patient identification, disease detection, and emotion recognition in healthcare environments. Some of the recent deep learning-based healthcare face analysis approaches are summarized in this section.

In 2020 Jin, B., et al., [21] suggested performing computer-aided facial diagnosis for a variety of illnesses utilizing deep transfer learning using facial recognition. Utilize a relatively small dataset to do computer-aided face diagnosis in the trials for both single (beta-thalassemia) and multiple disorders (beta-thalassemia, hyperthyroidism, Down syndrome, and leprosy). The success of deep transfer learning applications in facial diagnosis with a limited dataset may lead to a low-cost, noninvasive approach to disease screening and detection.

In 2021 Onyema, E.M., et al., [22] described a method for recognizing facial expressions using the convolutional neural network (ConvNet), a deep learning algorithm. For training, samples of seven common face expressions were gathered from the FER2013 dataset. The proposed approach comes to the conclusion that by enhancing accuracy, visual identification, and interpretation of facial ideas and traits, deep learning-enabled systems for facial expression recognition improve the health sector's efficiency and prediction.

In 2020 Salama AbdELminaam, D., et al., [23] created a comprehensive FR system utilizing cloud and fog computing transfer learning. Deep convolutional neural networks (DCNN) are used in the developed system because to the dominating representation. According to all parameters, experimental findings demonstrate that the suggested approach outperforms alternative methods. The proposed approach outperforms the comparator algorithms in terms of accuracy (99.06%), precision (99.12%), recall (99.07%), and specificity (99.10%).

In 2021 Akter, T., et al., [24] proposed a transfer learning-based paradigm for autism face recognition to more precisely identify young children with ASD. Additionally, based only on autistic image data, our classifier identifies different ASD categories using the k-means clustering technique. The suggested method enhanced MobileNet-V1 model exhibits the best accuracy of 90.67% and the lowest value of both fall-out and miss rate of 9.33% when compared to other classifiers and pre-trained models. The improved MobileNet-V1 model showed the best accuracy (92.10%) for k = 2 autism subtypes.

In 2024 Mutawa, A.M. and Hassouneh, A., [25] suggested using machine learning, an optical flow algorithm, and electroencephalography (EEG) to develop a multimodal intelligent real-time emotion recognition system. Four-band virtual power channels—alpha (8–13 Hz), beta (13–30 Hz), gamma (30–49 Hz), and theta (4–8 Hz)—were employed with 14 EEG inputs. reached a maximum recognition rate of 87.25 % with only EEG data and 90.25 % using only face landmarks. 99.3% accuracy was attained in a multimodal approach when both the face and EEG streams were analyzed.

According to the literature review, various face recognition methods focus on conventional feature extraction and single-modal learning, which limits the ability to capture complex facial patterns under different healthcare conditions. Traditional classifiers are used in many existing models, which exhibit poor performance in case of poses, illumination variations, occlusion and facial expressions. Furthermore, several methods have poorer recognition performance and higher misclassifications in a real-time patient monitoring context. These constraints decrease the reliability and efficiency of automated health care patient management systems. To overcome these challenges, a potential solution is to combine MediaPipe Face Mesh with a deep learning model, a CNN reliably cutting facial landmarks and recognize faces intelligently within medical contexts.

3. PROPOSAL CNN-MPFM METHODOLOGY

This section proposes a DL-based Convolutional Neural Network with MediaPipe Face Mesh (CNN-MPFM) for healthcare face recognition framework for better patient identification and monitoring in healthcare settings. The architecture includes patient image acquisition devices, patient image preprocessing modules, face landmark detection and intelligent classification to guarantee the reliable analysis of patient healthcare data. The captured facial images are transmitted to the processing unit, where image normalization and face alignment are applied, followed by MediaPipe Face Mesh based facial landmark extraction. Extracted facial features are then forwarded to CNN classification network to identify meaningful facial patterns and patient conditions. Based on the learned representations, the facial images are categorized into normal and suffocated classes. Overall workflow of developed CNN-MPFM system is shown in Figure 1.

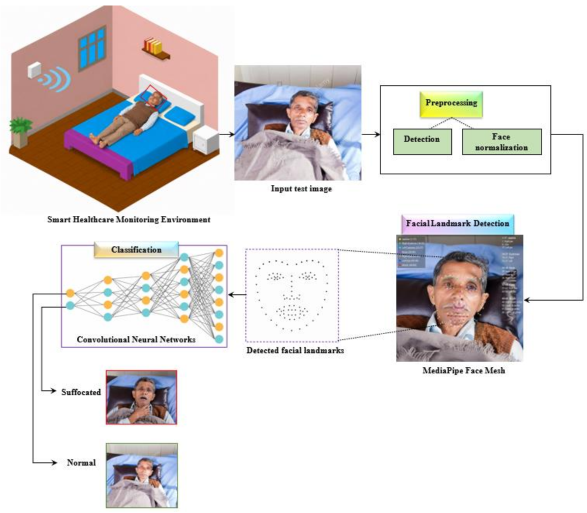

Figure 1. Overall workflow of Proposed CNN-MPFM model

3.1 Preprocessing

Input image is captured from the patient monitoring camera and used for facial feature analysis in the proposed CNN-MPFM healthcare system. The process of preprocessing is carried out to prepare the captured facial image data for analysis. This image data is organized by means of face detection and normalization to obtain uniform scaling. The process improves the quality of facial images and enhances performance of proposed healthcare monitoring model.

3.1.1. Face Normalization

The most common normalizing method which changes all the input values into a single value whose average is zero and its standard deviation is one. The SD and mean are calculated of each property. Each value of an attribute X is normalized using the calculated standard deviation and its mean. The transformation equation is the following:

$$Z = \frac{Y-\beta}{\delta} \tag{1}$$

Where β = mean of attribute Y and δ = SD of attribute Y. This method's benefit stems from its ability to lessen the impact of outliers on the data.

3.1.2. Face detection

A few basic statistical methods were used to begin machine face detection. Among them, Eigenfaces was one of the most well-liked. It represents every image as a vector of weights obtained by projecting on eigenfaces components. Even though statistical techniques are not very effective, they provide assurance that the machine can identify a human face without intervention from other sources. It has a lasting effect on future advancement.

3.2 Facial Landmark Detection

Proposed healthcare monitoring system is implemented with Python and OpenCV. The suggested approach uses Face Mesh to identify and locate face landmarks using Google's MediaPipe library. For real-time applications, MediaPipe library is effective and pre-trained. Face Mesh method uses a two-step neural network process to extract from a two-dimensional facial image the exact three-dimensional coordinates of 468 points an individual's face. BlazeFace, the first network, uses full image analysis to identify faces. In order to locate landmarks, the second network works inside the identified face region. The pipeline as a whole may operate in real time on common devices and is geared for high-speed processing. Moreover, the framework can track previous facial crops for continuous facial landmark tracking, so that the power and memory consumption and CPU usage are reduced. These facial landmarks are then extracted and used for intelligent patient condition analysis.

3.2.1 MediaPipe Face Mesh

MediaPipe Face Mesh is highly developed technique that offers an ongoing set estimated directs for key facial landmarks in real-time and identifies key facial landmarks. This technique is able to determine the 3D surface of a person without the need of a depth sensor. The Face Mesh module is based on the BlazeFace framework, which leverages the MobileNetV2 and SSD detector frameworks to optimize for mobile GPU inference. The integration of MediaPipe Face Mesh landmarks into more extensive healthcare monitoring systems is made easier by Google's computer software development kits (SDKs) and application programming interfaces (APIs). The model was developed using the TensorFlow framework, which allows users to retrain or adjust the model according to the requirements of their application. This is advantageous because it realistically represents the motion of the facial landmarks and deformation of the facial structure in real time. Using predetermined landmarks makes it easier to analyze facial regions such as the eyebrows, eyes, lips, nose, and jawline. Variations in important facial places can be utilized for intelligent patient condition monitoring and classification.

3.3 Patient Condition Classification using CNN

CNN is used for accurate patient condition categorization by learning important facial features and patterns from the extracted face mesh data. One-dimensional (1-D) Convolutional Neural Network, a well-known deep neural network, is utilized in the proposed CNN-MPFM approach as convolution kernels only scan the logging curves' depth direction. Convolutional, pooling, and fully linked layers make up the CNN. CNN uses convolution and pooling processes to extract implicit characteristics from input data. After that, a completely linked layer receives the combined extracted characteristics. Finally, Figure 2 shows how an activation function is employed to give a neuron's output nonlinearity.

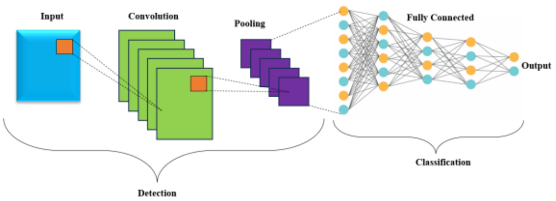

Figure 2. Basic CNN architecture

A crucial component of the CNN is the convolution layer. Each convolutional layer has several convolutional kernels that are convolved with input data in order to extract hidden features and create feature maps. The convolutional layer's output is generated by passing the feature maps through a non-linear activation function. The following is an expression for the convolutional layer:

$$d_i = r(e_i * y_i + b_i) \tag{2}$$

where y_i shows input of layer of convolution. d_i is i^{th} feature map output, e_i is a matrix of weights, * shows dot product, b_i is bias vector, and $r\ (\cdot)$ shows activation function. A common choice for CNN activation functions is rectified linear unit (ReLU) function. ReLU is defined mathematically as:

$$d_i = r(g_i) = max(0, g_i) \tag{3}$$

where g_i is a component of feature maps that are produced by convolutional procedures. The pooling operation's purpose is to reduce feature map size and avoid overfitting. One of the most used pooling techniques is max pooling. This is accomplished to determine the highest value of a designated area in feature maps.

$$\gamma(d_i, d_{i-1}) = max\ (d_i, d_{i-1}) \tag{4}$$

$$p_i = \gamma(d_i, d_{i-1}) + \beta_i \tag{5}$$

where $\gamma\ (\cdot)$ is maximum subsampling function for pooling. Bias is represented by β_i while the output of the max-pooling layer is indicated byp_i. The final output vector is then calculated by the fully linked layer after receiving feature maps produced by convolutional and pooling processes, as seen under:

$$y_i = r(t_i p_i + \delta_i) \tag{6}$$

where y_i shows concluding output path, δ_i is the bias, and t_i is a weight matrix. CNN model finds accurate classification of patient conditions into normal and suffocated classes based on extracted facial features.

4. RESULT AND DISCUSSIONS

In this section, presented CNN-MPFM method is evaluated and compared with existing frameworks. CNN-MPFM proposed method is implemented through a regular computing environment using Python based frameworks. To verify the effectiveness of the CNN-MPFM anticipated model, evaluation metrics of accuracy, precision, recall, and F1-score are hand-me-down to measure performance.

4.1. Evaluation metrics

Typical is estimated based on standard evaluation measures that include accuracy (ACY), recall (RCL), precision (PCN), and F1-score (F1S) that offer a thorough examination of intrusion detection capabilities.

$$ACY = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

$$PCN = \frac{TP}{TP+FP} \tag{8}$$

$$RCL = \frac{TP}{TP+FN} \tag{9}$$

$$F1S = 2\left(\frac{precision * recall}{precision+recall}\right) \tag{10}$$

Whereas FP and FN indicate false positive and negative cases, TP and TN indicate true positive and negative cases.

Table 1. Performance Analysis of Proposed CNN-MPFM Model

Classes	ACY (%)	PCN (%)	RCL (%)	F1S (%)
Normal	99.58	99.52	99.55	99.53
Suffocated	99.46	99.4	99.44	99.42
Average	99.52	99.46	99.49	99.47

Table1 shows the proposed CNN-MPFM model achieves effective patient condition classification. For the Normal class, it attains 99.58% accuracy and 99.53% F1-score. For the Suffocated class, it obtains 99.46% accuracy and 99.42% F1-score, showing reliable detection performance. The overall average results of 99.52% accuracy, 99.46% precision, 99.49% recall, and 99.47% F1-score confirm efficiency of proposed healthcare monitoring system.

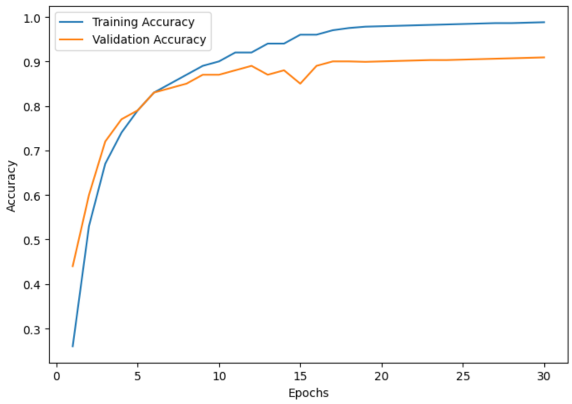

Figure. 3 Training and Validation Accuracy

Figure 3 indicates accuracy curve of proposed CNN-MPFM method. Training accuracy increases from 26% at initial epoch to 98.8% at the final epoch, demonstrating strong learning performance. Likewise, the validation accuracy improves from 44% to 90.9%, indicating good generalization ability on unseen data. The consistent improvement in training and validation accuracy confirms effectiveness of proposed method for patient condition classification.

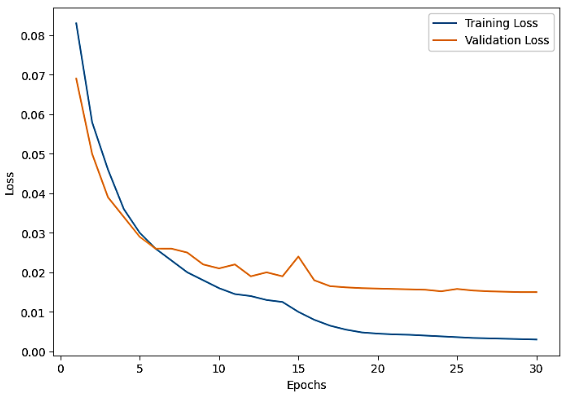

Figure. 4 Training and Validation Loss

Suggested CNN-MPFM model's loss curve over 30 training epochs is shown in Figure 4. Effective model learning is demonstrated by the training loss, which dramatically drops from 0.083 in the first epoch to 0.003 in the last. Similarly, the validation loss also drops from 0.069 to 0.015, and the amount of classification error is minimal, leading to continued convergence. The gradual reduction in the number of losses demonstrates the model's robustness and optimization potential.

Table 2. Comparative analysis of existing and proposed CNN-MPFM method

Authors	**Methods**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Jin et al. (2020)	Deep Transfer Learning	91.25	90.84	90.96
Onyema et al. (2021)	ConvNet	93.4	92.85	93.12
Akter et al. (2021)	MobileNet-V1	92.1	91.76	91.94
Mutawa et al. (2024)	EEG + Facial Landmarks	99.3	99.12	99.18
Proposed CNN-MPFM Model	CNN-MPFM	99.52	99.46	99.49

Table 2 depicted in proposed CNN-MPFM model gets the best accuracy of 99.52%, precision of 99.46%, and recall of 99.49%.The proposed model achieves improved patient condition classification accuracy over the state-of-the-art approaches like Deep Transfer Learning, ConvNet and MobileNet-V1.These findings demonstrate how well CNN and MediaPipe Face Mesh can be integrated for intelligent healthcare monitoring applications.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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