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FACE RECOGNITION: IN HEALTHCARE

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ABSTRACT

This review paper provides a comprehensive examination of facial recognition technology in healthcare, exploring its diverse applications such as patient identification, monitoring, disease diagnosis, and personalized treatment plans. The discussion encompasses technical advancements, challenges, and ethical considerations associated with its implementation.

The paper highlights the potential for improved accuracy and efficiency in patient identification and access control, as well as its role in monitoring physiological parameters and facilitating remote patient monitoring. Integration with electronic health records (EHRs) is explored for enhanced patient management. Technical challenges, including issues related to accuracy, security, and interoperability, are critically addressed. Ethical implications, such as privacy concerns and the responsible use of patient data, are discussed to emphasize the importance of ethical considerations in the deployment of facial recognition technology in healthcare. The review concludes by outlining future research directions, advocating for a proactive and collaborative approach to ensure the responsible and ethical implementation of facial recognition technology in healthcare settings.

Index Terms—Facial recognition, healthcare applications, patient identification, remote monitoring, EHR integration, disease diagnosis, treatment planning, technical challenges, accuracy, security, interoperability, ethical considerations, privacy, responsible data use, convolutional neural networks, self- organizing feature maps, Karhunen–Loève transforms, hybrid systems, access control, pattern recognition, image classification, future research.

1. INTRODUCTION

The paper critically examines the transformative potential of facial recognition technology in healthcare, particularly in enhancing patient care and mitigating medical errors.

Delving into its versatile applications, including patient identification, monitoring, and diagnosis, the authors underscore the technology's capacity to revolutionize hea lth care practices. Despite these promises, how ever, the discussion discerningly addresses significant concerns surrounding the accuracy and privacy of facial recognition systems within healthcare settings. The authors meticulously analyze recent approaches and challenges inherent to facial recognition in the healthcare domain, providing a comprehensive overview of the existing literature (here).

In response to these challenges, the paper systematically presents and evaluates a range of techniques proposed in the literature. These techniques are designed to address and rectify issues related to accuracy and privacy, ensuring a thorough examination of the strategies available to mitigate potential pitfalls.

The dual focus on both the promise and challenges of facial recognition technology in healthcare, along with the insightful exploration of proposed solutions, positions the paper to contribute meaningfully to the ongoing discourse surrounding the responsible and effective implementation of facial recognition systems in the healthcare landscape (here).

This paper delineates two distinct scenarios relevant to facial recognition applications. The first scenario involves the task of identifying a person within an extensive database of faces, such as those found in police databases. In this context, the systems typically generate a list of the most probable matches, and real- time processing is generally not imperative. Conversely, the second scenario focuses on real-time applications, such as security monitoring systems or access control systems where rapid identification is essential.

Here, the goal is to either identify specific individuals in real-time or enable access for a predefined group while denying it to others, as exemplified in building or computer access scenarios [8]. Unlike the first scenario, multiple images per person are often accessible for training purposes, and real-time recognition becomes a crucial requirement. In this paper, the primary emphasis is on the second scenario, specifically addressing the challenges and nuances associated with real-time facial recognition in various conditions, including variations in facial detail, expression, and pose.

The authors explicitly exclude considerations for invariance to extensive rotation or scaling, assuming the availability of minimal preprocessing when necessary. The paper underscores the need for efficient algorithms for facial location,

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2. LITRRATURE SURVEY

Utilizing the ORL database with facial images captured from April 1992 to April 1994 at the Olivetti Research Laboratory, our study did not include experiments necessitating the system to reject individuals not part of a designated group, a vital consideration for applications like building access control.

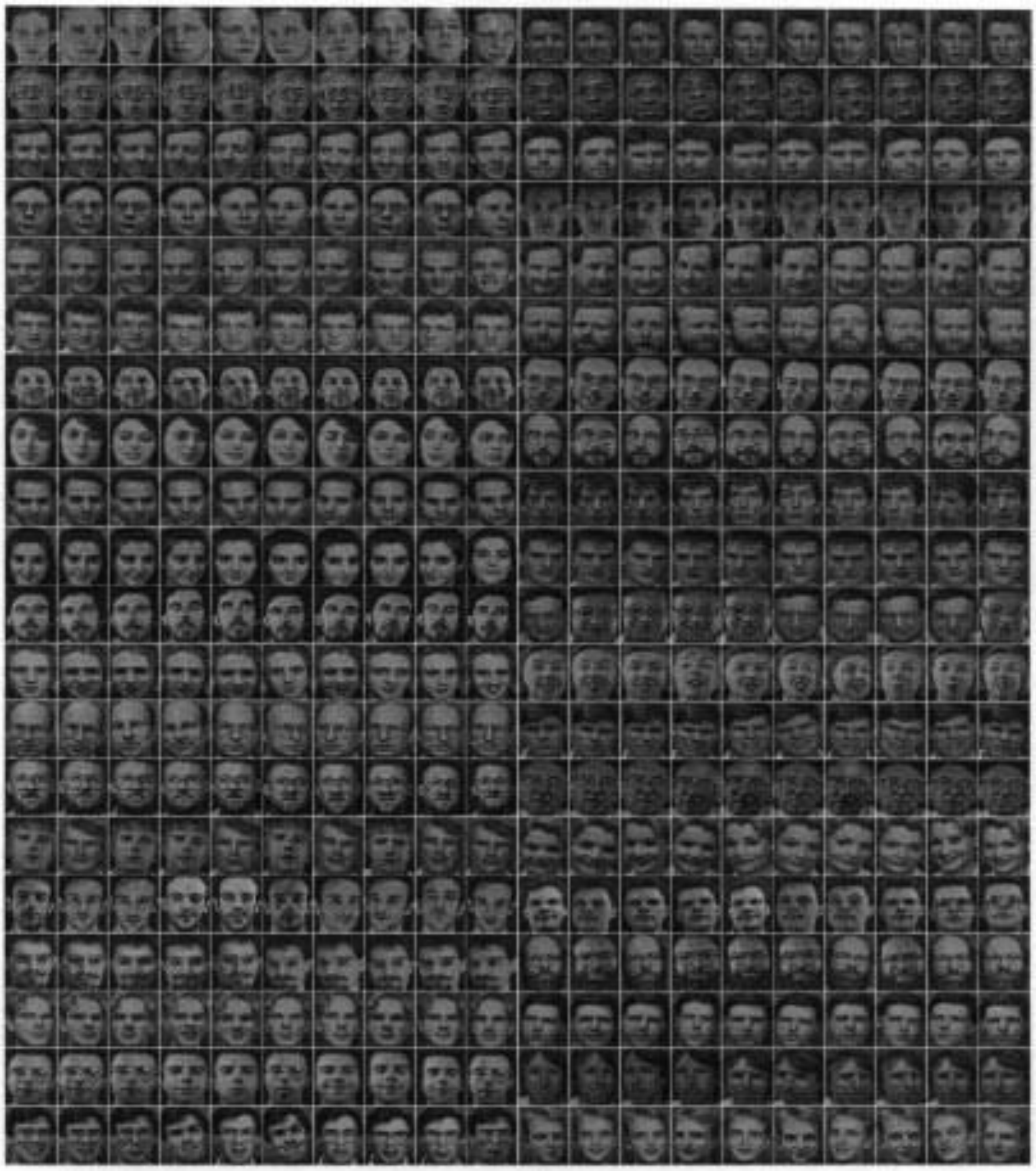

Fig. 1. The ORL face database. There are ten images each of the 40 subjects.

Captured at the Olivetti Research Laboratory in Cambridge, U.K., the ORL database comprises ten distinct images for each of the 40 subjects. Some subjects' images were taken at different times, reflecting variations in facial expressions (open/closed eyes, smiling/nonsmiling) and facial details (glasses/no glasses). All images were consistently captured against a dark homogeneous background, with subjects positioned upright, allowing for minor tilting and rotation, up to about 20 degrees. Additionally, there is a slight scale variation of approximately 10%. Figure 1 displays thumbnails of all images, offering a visual overview of the dataset's richness and diversity. The ORL database, sourced from the Olivetti Research Laboratory in Cambridge, U.K., features ten distinct images for each of its 40 subjects. Capturing temporal variations with images taken at different times, the dataset showcases diverse facial expressions (open/closed eyes, smiling/nonsmiling) and details (glasses/no glasses). Ensuring consistency, all images were taken against a dark homogeneous background with subjects positioned upright, allowing slight tilting and rotation, up to 20 degrees. The dataset's realism is heightened by a 10% scale variation. Figure 1 provides thumbnails, offering a visual glimpse into the dataset's rich and varied content, making it a valuable resource for authentic exploration of facial recognition challenge.

Fig. 2. Data from 2019

AI integration strategy in clinical practice isn't always taken warmly. The reputation precedes AI and most people see it racially-biased, weirdly inhuman, and threatening to traditional jobs. But is it? It has drawbacks as most novel technologies do, but its pros do outweigh the cons.

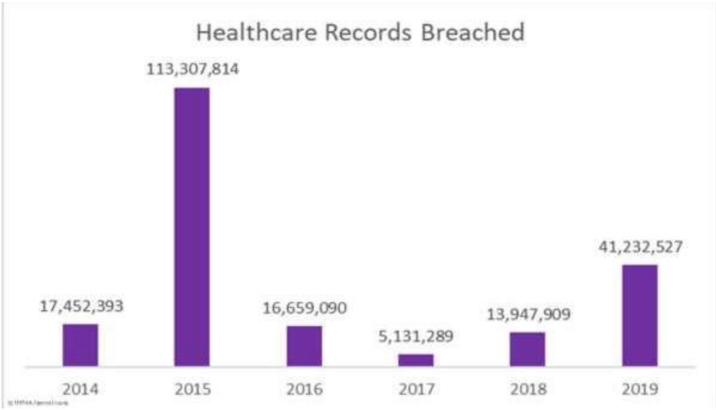

Fig.3

The 36.12% annual increase in reported data breaches, soaring from 371 incidents in 2018 to 505 breaches in 2019, highlights a heightened concern for the security of sensitive information. Faced with millions of compromised records, healthcare institutions are actively pursuing robust solutions to bolster patient data protection. Artificial Intelligence (AI) plays a crucial role in this effort, providing advanced tools for secure data transfer and enhanced reliability.

Within healthcare environments, the strategic integration of Artificial Intelligence (AI) assumes a central role as a proactive measure to bolster data security. Healthcare institutions and providers are progressively leveraging the advanced capabilities of AI, not solely for identifying and responding to potential threats, but also for the automation of intricate processes such as malware analysis and threat intelligence. This proactive utilization of AI gains particular significance in the context of the ongoing digitization of healthcare records. As patient information transitions to digital platforms, the imperative adoption of AI-driven solutions emerges to safeguard the confidentiality and integrity of sensitive medical data. The comprehensive role of AI extends beyond conventional threat detection, encompassing robust support in managing the complexities inherent in evolving cyber threats. Through the automation of critical processes like malware analysis and threat intelligence, AI systems not only expedite response times but also enhance the overall efficiency of security protocols. This strategic integration stands as a linchpin in fortifying the resilience of healthcare systems, empowering them to navigate the progressively sophisticated landscape of cyber threats. In essence, the incorporation of AI into healthcare practices signifies a forward-thinking and indispensable measure aimed at ensuring the security of patient information and maintaining the integrity of healthcare data systems.

Key Use Cases of Face Recognition in Healthcare

A. Patient Check-In and Check-out Procedure

Recent developments in patient identification solutions have garnered substantial attention for their ability to streamline the entire patient check-in process, liberating hospital personnel from cumbersome paperwork. Crucially, solutions based on face recognition technology play a pivotal role in ensuring accurate patient identification, thereby mitigating the risk of incorrect procedures and wrong-patient errors. The repercussions of such errors can be severe, ranging from temporary harm to permanent damage or even death.

B. Diagnosing Disease and Conditions using Face Recognition

Face recognition is integral to healthcare diagnostics, with the emergence of "health mirrors" that utilize lights to measure vital signs. This technology, accessible through laptops or phone cameras, brings healthcare closer to homes, especially with the rise of telemedicine. Face recognition health apps enable individuals to assess their health status with a simple face scan, measuring metrics like heart rate, blood pressure, and stress levels. Notably, this contact-free and non-invasive approach is advantageous, particularly for checkups involving children or individuals with sensitive skin.

Fig. 4. Diagnosing disease and Conditions using Face Recognition. .

What is FRT?

Facial recognition technology (FRT) is a method that identifies a person based on specific facial features, including bone structure and skin texture. Its functional algorithm relies on databases, comparing features to produce results. While FRT has been used to identify law offenders and visualize how missing children might age, its application in healthcare is relatively recent. The sophistication and accessibility of FRT, thanks to larger face databases and its integration into everyday devices like phones, make it increasingly appealing in medicine. It offers various implementation possibilities in healthcare, ranging from reducing paperwork to assisting physicians in diagnosis.

From Facebook picture-tagging to identifying rare genetic conditions: how can FRT benefit healthcare?

Do you know how Facebook or your mobile prompts you with suggestions about people to tag in a photo? This is a prime example of FRT in action – the software can identify someone based on their unique facial features. Now imagine going to your local hospital in the near future for that sore throat that has been bothering you for over a week.

Instead of going through the waiting lines for administrative purposes, a virtual assistant will scan your face in a matter of seconds and assign you to your doctor. In so doing, the algorithm can even detect other irregularities like signs of depression and will inform your doctor of such a possibility.

Such applications are far from being mere products of the mind. An oft-cited example is Face2Gene, an app used by clinicians that can detect rare genetic conditions like Cornelia de Lange syndrome, where patients have characteristic facial features which can be missed by physicians because they simply might not have come across it during their clinical practice.

This was the case with Omar Abdul-Rahman, a medical geneticist, who, thanks to the app, recommended the family of a three-year-old boy that they order a specific genetic test for Mowat-Wilson syndrome, which returned positive. “If it weren’t for the app I’m not sure I would have had the confidence to say ‘yes you should spend $1000 on this test,”

Rahman told the online outlet Leapsmag. This saved the family from making further expenses which might not have correctly identified the condition and would have further delayed the appropriate care that the young boy required.

In a study, the deep-learning algorithm DeepGestalt, which powers Face2Gene was shown to outperform clinicians in diagnosing syndromes like Noonan syndrome. DeepGestalt even correctly identified conditions in its top ten list 91% of the time. “It’s like a Google search,” the study’s co-author Karen Gripp tells Nature. With such a high success rate and the ease of using the app, such a comparison is not far-fetched.

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What about the future of healthcare?

It wouldn't even be worthless to speculate what this technology could lead to or do in the future. Below are our top 5 potential and highly anticipated uses of FRT in healthcare in the (near?) future:

1. Smart mirrors

   "Mirror, Mirror on the Wall, Am I Healthy?" Asking your mirror this question might soon be possible. By combining FRT into a seemingly simple mirror with a built-in camera and existing technologies like SkinVision's skin analysis and Nuralogix's transdermal optical imaging technique to measure blood pressure and stress level, a quick scan can reveal a lot by simply looking at your own reflection (or by asking your mirror!). Such a smart mirror could advise you to get that new mole on your cheek checked, recommend meditation in case your stress level is higher than usual and refer you to your doctor if there are any abnormal fluctuations in your blood pressure.

2. Care for healthcare professionals

   More than just for patients' health, FRT can also be used for the wellbeing of healthcare practitioners themselves. Medscape's 2022 report found that 47% of physicians feel burned out, 64% were colloquially depressed and 24% suffered from clinical depression. These can be identified via facial analysis and subsequently addressed, like suggesting stress-relieving measures like yoga or even vacations, before they further affect

   the health of healthcare providers.

3. Looking for mischief

   The applications of such technology can further be adapted to other areas within the healthcare system. For example, unlawful people like insurance imposters, drug seekers and criminals can be easily identified from a given database and dealt with accordingly.

4. Touchless access control

   Access control will probably become the most typical use of facial recognition technology: it limits surface contact (and thus disease transmission) while allowing accelerated admission to office buildings, and can be used in many work-related areas: allowing dedicated team members to enter departments, operate turnstiles, or access other entry points with their face. As face recognition was developed to identify users even with a face mask on, it can be a valuable ally in pandemic situations.

5. Mask detection

   Facial recognition systems are also capable of recognising people not wearing / not properly wearing a mask in a setting where it is mandatory, and notify the person, or the authorities if necessary.

   More information (here)

   Patient identification is a critical aspect of healthcare settings to prevent errors and enhance patient safety. Traditional methods like RFID, fingerprint scanners, and iris scanners have limitations, prompting the development of alternative solutions. This study focuses on the creation of a facial recognition mobile app as an improved patient verification method The app, designed for simplicity and efficiency, encompasses features such as registration, medical records, examinations, prescriptions, and appointments. Evaluation involving 62 pediatric patients demonstrated the app's high accuracy (99%) in verifying patients, even in cases of unconsciousness.

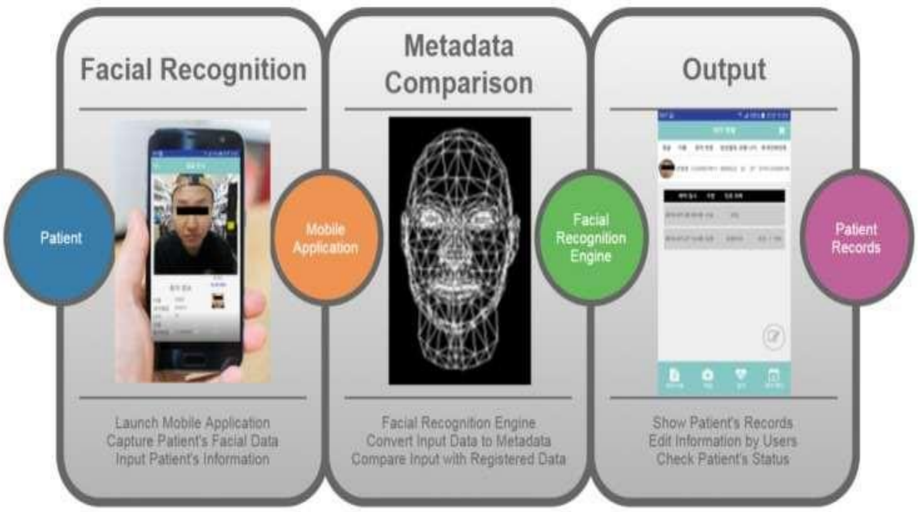

Fig.5

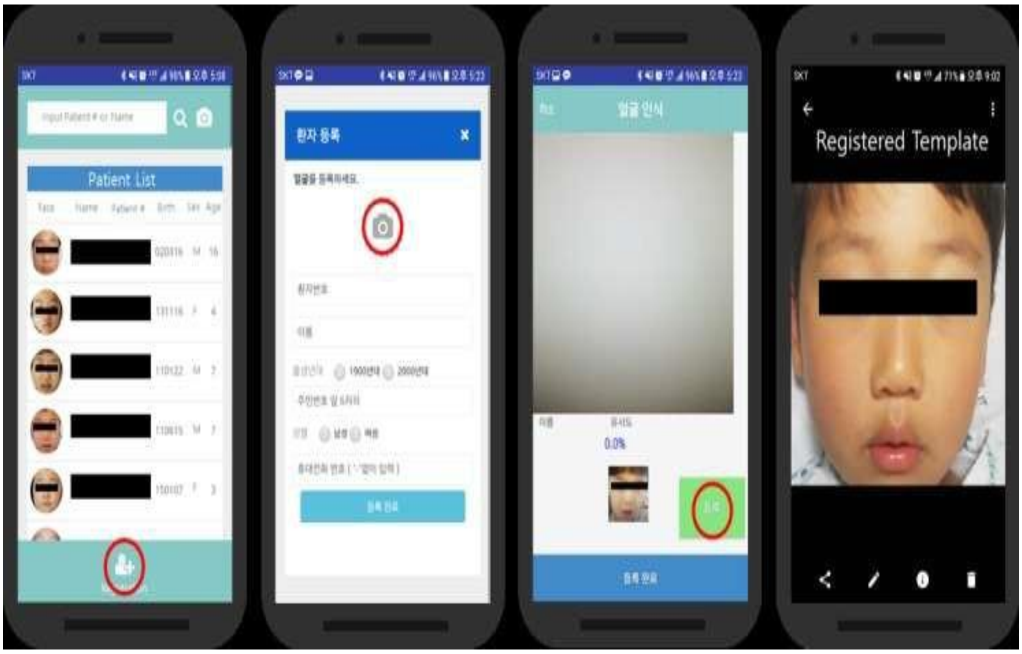

Fig.6

Table 1

Number of outpatient verification trial results.

Characteristic		Pass verification, n	Fail verification, n
Age (years)			
	0-10	28	0
	11-20	2	0
Sex			
	Male	19	0
	Female	11	0
Facility visit[a]			
	Male	86	0
	Female	50	0

Fig. 7. The above figures is available in (here) and (here) and (here)

The app's interface is tailored for user-friendliness, featuring key functionalities for seamless data collection. Its successful To track a patient using the facial recognition mobile app, the performance in both outpatient and inpatient settings positions it process involves capturing the patient's facial image for as a promising alternative for patient identification, addressing comparison with registered data. On the main screen of the app, issues associated with traditional methods. The facial recognition there is a camera button located at the upper right corner (refer to app offers a versatile and accurate solution that has the potential Figure 3). The steps for capturing the patient's facial data and to reduce costs and enhance accuracy in healthcare scenarios, comparing it with the registered data are illustrated in the center especially where conventional methods may prove impractical or of Figure 3. The last image in fall short. In summary, this study introduces a facial recognition mobile app depicting a successfully identified patient. as a viable and accurate alternative for patient identification in Given that the research was conducted at a children's hospital healthcare settings. Its robust performance, particularly in specializing in plastic surgery for correcting burns, birth defects, scenarios involving unconscious patients, highlights its potential etc., the average patient age was 5 years. Each patient, on average, to improve patient safety and streamline identification processes. visited 4 different hospital facilities, using the facial recognition The mobile app presents a practical solution to the limitations mobile app to verify their identification

associated with traditional patient verification methods in healthcare.

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3. METHODOLOGY

This study delves into the burgeoning field of machine learning algorithms applied to facial expression recognition, with a primary focus on the convolutional neural network (ConvNet) deep learning approach. Leveraging the FER2013 dataset, which encompasses samples of seven universal facial expressions, the research aims to enhance recognition accuracy without the computational overhead associated with intricate CNN layering. The study's key contribution lies in addressing the challenge of high computational costs while providing a model that approaches the accuracy achieved by state-of-the-art alternatives in facial expression recognition. By optimizing the ConvNet model architecture, the research seeks to offer a more computationally efficient yet accurate solution.

In examining related works, various methodologies have been explored. Studies like Hussain and Al Balushi introduced inception layers with different convolution layers, attaining an accuracy of 0.693. Suryanarayana et al. utilized the Hist-eq technique, achieving consistent results with an accuracy of 0.6667. Zhang et al. proposed a cross-dataset approach, combining features from multiple datasets for an accuracy of

0.71. In this context, the research introduces the application of ResNets, focusing on automatic facial expression classification to enhance accuracy. This segment serves to provide an overview of existing methodologies, laying the groundwork for the novel approach introduced in the current study.

The methodology section details the specifics of the models and techniques employed for facial expression recognition. Data augmentation strategies are applied to the FER2013 dataset to enrich sample diversity, and a ConvNet model is enhanced by introducing a residual block. Paramount to the methodology is the optimization of parameters to improve the learning capabilities of the model. This section elucidates the steps taken in model development, data preprocessing, and parameter optimization. The synergy between data augmentation and ConvNet architecture modifications is a critical aspect of the proposed method, contributing to its efficacy in facial expression recognition.

In summary, this study encapsulates the essence of applying ConvNets to facial expression recognition, providing a computationally efficient yet accurate alternative. By reviewing related works, it contextualizes the research within the broader landscape of existing methodologies. The detailed methodology section sheds light on the specific techniques employed, emphasizing the fusion of data augmentation and ConvNet enhancements to achieve improved accuracy in facial expression recognition.

Fig. 8. Diagram of algorithm (here)

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In this phase, we detail the methodologies employed for facial expression recognition, incorporating diverse data augmentation strategies applied to the FER2013 dataset to enhance sample diversity. Concurrently, a Convolutional Neural Network (ConvNet) model is meticulously crafted, featuring the integration of a residual block to augment its capacity for nuanced feature extraction and heightened recognition accuracy. The methodology entails a thoughtful parameter selection process, where distinct parameter sets are chosen to optimize the model's efficiency and learning capabilities. This holistic approach, illustrated in the provided figure, underscores our commitment to advancing facial expression recognition through a synergistic blend of cutting-edge ConvNet design, strategic data augmentation, and parameter optimization.

Neural Network Model

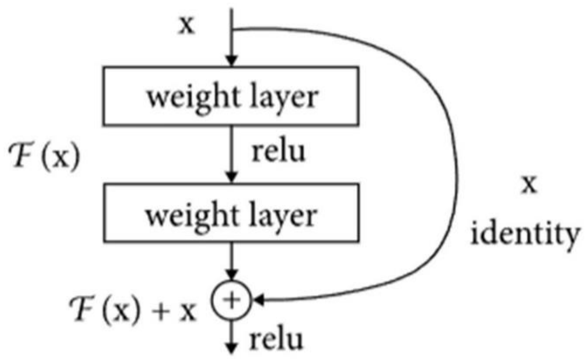

Fig. 9.

Our research employs a Convolutional Neural Network (CNN) model based on Residual Networks (ResNets) architecture, addressing challenges related to the vanishing/exploding gradient issue during the model's layer expansion. ResNets incorporate skip connections within residual blocks, allowing direct connections of specific layers to the output layer, thus improving computational efficiency by skipping certain layers. Our model configuration includes a pooling layer, two 64 × 64 convolutional layers, an initial ResNet block, a 512 × 512 convolutional block, a 128 × 128 convolutional layer, another pooling layer, and a final 512 convolutional layer with an associated pooling layer. We utilize the rectilinear activation function and introduce batch normalization to reduce internal covariance, ensuring stability and preventing overfitting in the model. This approach enhances the learning capacity of the model and addresses the challenges posed by the increasing number of layers.

4. RESULTS AND DISCUSSION

In this section, we will mention the results deduced on implementation of the methods mentioned in the proposed work. Figure 4 shows the confusion matrix that includes the accuracies per class as well as overall accuracy on FER2013 dataset. As shown in the confusion matrix, our model attained an accuracy of 0.70 which is very close to the state-of-the-art model that already exists but just with a fewer number of layers. Figure below shows accuracy on the test set after training the model.

Below figures are results obtained in(here) and (here)

Classification report for FNN :

	precision	recall	f1-score	support
0	0.63	0.64	0.63	491
1	0.80	0.73	0.76	55
2	0.60	0.55	0.57	528
3	0.89	0.88	0.88	879
4	0.53	0.56	0.55	594
5	0.83	0.82	0.82	416
6	0.67	0.68	0.67	626
accuracy			0.70	3589
macro avg	0.71	0.70	0.70	3589
weighted avg	0.70	0.70	0.70	3589

Fig.10

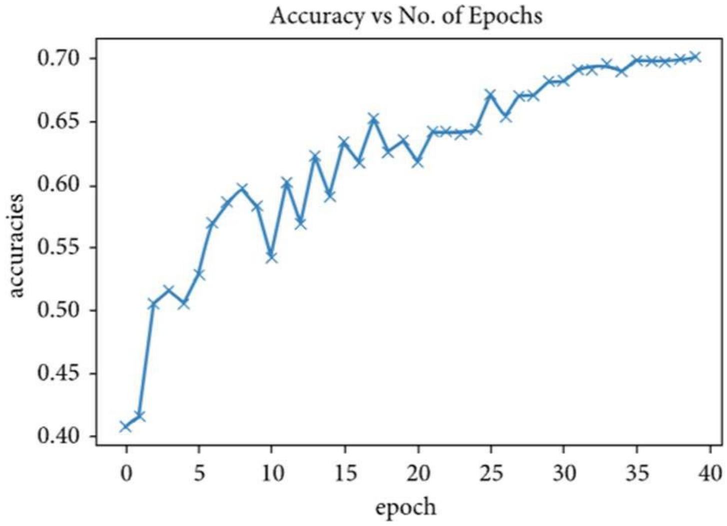

Fig.11

5. CONCLUSIONS

The paper delves into the multifaceted landscape of facial recognition technology in healthcare, meticulously examining its transformative potential, applications, challenges, and proposed solutions. By spotlighting real-time scenarios and the intricate nuances of facial recognition, particularly in variations of facial detail, expression, and pose, the authors provide a comprehensive overview. The inclusion of the ORL database underscores the practical evaluation of facial recognition techniques. The integration of artificial intelligence in healthcare for data security resonates with the contemporary concern of rising data breaches. Key use cases, such as patient check-in procedures and disease diagnosis through "health mirrors," illustrate the tangible benefits of facial recognition. The introduction of a facial recognition mobile app as a patient identification alternative adds a practical dimension, showcasing high accuracy, especially in scenarios involving unconscious patients. In essence, the paper bridges theoretical discussions with real-world examples, offering a forward-looking perspective on potential applications. The dual emphasis on promises and challenges contributes meaningfully to the discourse, making the paper a comprehensive and valuable resource in the ongoing dialogue on responsible and effective facial recognition implementation in the evolving landscape of healthcare.

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